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Signal processing for the measurement of the results of the Timed-Up and Go test using sensors

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Dedicatory

"The important thing is not to win every day, but always to fight."

Waldemar Valle Martins

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"The impossible exists until someone doubts it and proves otherwise."

Albert Einstein

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List of Publications

List of articles included in the dissertation resulting from this master's research programme

1. Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, Gonçalo Marques, Nuno M. Garcia, Nuno Pombo, Susanna Spinsante, and Eftim Zdravevski, "Is The Timed-Up and Go Test Feasible in Mobile Devices? A Systematic Review", published in Electronics 2020, 9, 528; (IF 2019: 2.412, Q1 Computer Science).

2. Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, Gonçalo Marques, María Vanessa Villasana, Nuno M. Garcia, Eftim Zdravevski, and Susanna Spinsante, "Identification of Diseases Based on the Use of Inertial Sensors: A Systematic Review", published in Electronics 2020, 9, 778; (IF 2019: 2.412, Q1 Computer Science).

3. Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, Nuno M. Garcia, Nuno Pombo, Susanna Spinsante, and Rute Crisóstomo. 2019. Smartphone-based automatic measurement of the results of the Timed-Up and Go test. In EAI International Conference on Smart Objects and Technologies for Social Good (GoodTechs '19), September 25–27, 2019, Valencia, Spain. ACM, Valencia, Spain, 4 pages. https://doi.org/10.1145/3342428.3343035

4. Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, María Vanessa Villasana, Rute Crisóstomo, Maria Canavarro Teixeira, and Eftim Zdravevski, "Mobile Computing Technologies for Health and Mobility Assessment: Research Design and Results of the Timed Up and Go Test in Older Adults". Sensors 2020, 20, 3481; doi: 10.3390/s20123481, June 2020 (IF 2019: 3.275, Q1 Instruments & Instrumentation).

5. Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, Nuno M. Garcia, María Vanessa Villasana, Petre Lameski, and Eftim Zdravevski, "Machine Learning Techniques with ECG and EEG Data: An Exploratory Study". Computers 2020, 9, 55; doi: 10.3390/computers9030055, June 2020 (Citescore 2019: 2.5, Q2 Computer Science).

6. Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, María Vanessa Villasana, Maria Canavarro Teixeira, and Eftim Zdravevski, “Experimental Study for Determining the Parameters Required for Detecting ECG and EEG Related Diseases During the Timed-Up and Go Test”. Computers 2020, 9, 67; doi: 10.3390/computers9030067, August 2020 (Citescore 2019: 2.5, Q2 Computer Science)

Other publications resulting from the master’s research programme not included in the dissertation

7. Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, María Vanessa Villasana, Nuno M. Garcia and Valderi Leithardt, “Detection of diseases based on Electrocardiography and Electroencephalography signals embedded in different devices: An exploratory study”, published in Brazilian Journal of Development, Curitiba, v. 6, n.5, p.27212-27231, may. 2020. (B2 - Qualis único 2019)

8. Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, Nuno M. Garcia and Eftim Zdravevski, “Non-Invasive Measurement of Results Of Timed Up And Go Test: Preliminary Results”. In Envelhecimento como perspetiva futura. Livro de atas do ageing congress 2019, 2019

Resumo

Os recentes avanços tecnológicos e o crescente uso dos dispositivos móveis tem permitido o surgimento de vários estudos em diferentes áreas da vida humana. Estes dispositivos estão equipados com diversos sensores que permitem adquirir diferentes parâmetros físicos e fisiológicos de diferentes indivíduos. Os dispositivos móveis apresentam-se com cada vez mais soluções, funcionalidades e capacidade de processamento. A presença de sensores nos dispositivos móveis, como o acelerómetro, magnetómetro e giroscópio, permite a aquisição de sinais relacionados com atividade física e movimento do ser humano. Em acréscimo, dado que estes dispositivos incluem possibilidade de ligação via Bluetooth, outros sensores podem ser utilizados em conjunto com os sensores incluídos no dispositivo móvel. O desenvolvimento deste tipo de sistemas inteligentes com sensores é um dos temas abordados no desenvolvimento de sistemas de *Ambient Assisted Living* (AAL). Diversas áreas da medicina têm beneficiado com estes avanços, proporcionando cuidados de saúde à distância, mas o foco desta dissertação é um dos testes funcionais focados na fisioterapia, o *Timed-Up and Go test*. O *Timed-Up and Go test* define-se como um teste muito utilizado por fisioterapeutas na recuperação de lesões e é constituído por seis fases, onde o individuo se encontra sentado numa cadeira, levanta-se, caminha três metros, inverte a marcha, caminha três metros e volta a sentar-se na cadeira.

O âmbito desta dissertação consiste na análise estatística e com inteligência artificial dos dados recolhidos durante a execução do *Timed-Up and Go test* com recurso a diversos sensores, sendo que para isso foi desenvolvida uma aplicação móvel que permite adquirir os dados de diversos sensores durante a execução do teste com pessoas idosas institucionalizadas. A dissertação foca-se na criação de um método de análise dos resultados do *Timed-Up and Go test* com recurso ao acelerómetro e magnetómetro do dispositivo móvel e um sensor de pressão, ligado a um dispositivo BITalino, posicionado na cadeira. Ao mesmo tempo, foram recolhidos sinais de sensores de Eletrocardiografia e Eletroencefalografia, conectados a outro dispositivo BITalino, para análise de diferentes problemas de saúde. Assim, implementaram-se métodos estatísticos e de inteligência artificial para a análise dos dados recolhidos a partir destes sensores com recurso ao procedimento experimental inicialmente executado.

Inicialmente, foi realizada a revisão da literatura relacionada com o *Timed-Up and Go test* e o uso de sensores, sendo que a revisão de literatura terminou com a identificação das doenças passíveis de serem identificadas com recurso aos sensores inerciais. Seguidamente, apresentou-se a proposta de arquitetura a ser utilizada para a recolha dos dados, tendo em conta os sensores anteriormente referidos. Os dados presentes neste estudo foram recolhidos de 40 idosos institucionalizados da região do Fundão (Portugal), equipados com um dispositivo móvel e um dispositivo BITalino, bem como os restantes sensores. Por fim, passou-

se então à análise dos dados recolhidos que foi dividida em 3 estágios, começando pela análise do acelerómetro, magnetómetro e sensor de pressão para identificação dos parâmetros do *Timed-Up and Go test*, utilizando métodos estatísticos para a análise dos dados recolhidos. No segundo estágio foram implementados métodos estatísticos para correlacionar as doenças passiveis de serem detetadas por sensores de Eletrocardiografia e Eletroencefalografia. Por fim, no terceiro estágio foram implementados métodos de inteligência artificial, *i.e.*, redes neuronais artificiais, para relacionar as doenças do foro cardíaco e nervoso com os dados dos diferentes indivíduos de modo a aferir as suas características.

Como trabalho futuro, os resultados apresentados nesta dissertação podem servir para a criação de sistemas de baixo-custo, e de acesso a todos os cidadãos, que permitam a deteção mais atempada de determinados distúrbios e possam servir de auxílio aos profissionais de saúde no diagnóstico e tratamento de doenças.

Palavras chave

Timed-Up and Go test, sensores, dispositivo móvel, fisioterapia, processamento de dados.

Resumo Alargado

Introdução

Este capítulo resume, de forma alargada e em Língua Portuguesa, o trabalho de investigação descrito na dissertação de mestrado intitulada de “*Signal processing for the measurement of the results of the Timed-Up and Go test using sensors*”. Inicialmente, este capítulo descreve o enquadramento da dissertação, o problema abordado e os objetivos desta dissertação de mestrado, bem como o enquadramento da mesma e as principais contribuições. Seguidamente, será apresentado um resumo de cada um dos capítulos desta dissertação, que correspondem às principais contribuições da mesma. O capítulo termina com a apresentação das principais conclusões desta dissertação, bem como a apresentação de algumas linhas de investigação para o futuro.

Enquadramento da dissertação

O crescente desenvolvimento tecnológico tem criado novas oportunidades de investigação nas mais diversas áreas da vida humana, sendo que muitas dessas áreas eram completamente heterogéneas, mas hoje apresentam cada vez mais pontos em comum [1]–[4]. O surgimento e desenvolvimento de sistemas com sensores cada vez de maiores capacidades e com mais funcionalidades tem vindo a permitir alargar amplamente o âmbito deste tipo de estudos [5]–[11].

O desenvolvimento rápido e cada vez maior no mercado de dispositivos móveis, nomeadamente dos smartphones que hoje apresentam maiores capacidades de processamento e cada vez mais funcionalidades e sensores incorporados [12]–[14], tais como acelerómetro, magnetómetro, giroscópio, entre outros, apresenta-se como uma excelente oportunidade ao desenvolvimento das mais diversas soluções nas mais diferentes áreas da vida humana [15]–[20]. Devido ao seu tamanho e fácil capacidade de desenvolvimento de aplicações, os sensores presentes nos dispositivos móveis apresentam-se como sensores com grandes e inúmeras capacidades que permitem o surgimento de oportunidades de desenvolvimento de soluções nas mais diversas áreas do conhecimento [6], [8], [21], [22].

O uso de sensores é útil em diversas áreas. Como os sensores permitem adquirir diversos parâmetros físicos e fisiológicos [5], [9], [19], [23]–[26], a fisioterapia é uma das áreas em eles podem ser úteis, conjuntamente com dispositivos móveis para aquisição de dados e cálculo automático dos resultados, contribuindo para uma identificação mais precisa dos resultados em vários testes [27]–[31]. Alguns dos testes mais comuns da fisioterapia que podem ser implementados com recurso a sensores são:

- O *Heel-Rise Test* é destinado a patologias relacionadas com doença venosa crónica, disfunções na perna na zona dos gémeos, ruturas ou tendinites no tendão de Aquiles, lesões desportivas, patologias neurológicas e ou degenerativas [32], [33];
- O *Functional Reach Test* é destinado a recuperações de patologias relacionada com lesões dos membros superiores, patologias neurológicas e/ou degenerativas e lesões desportivas [21], [34];
- O *Ten Meter Walk Test* procura ajudar na recuperação de patologias relacionadas como alterações de equilíbrio, patologias neurológicas e/ou degenerativas, lesões dos membros inferiores e doença venosa crónica [35], [36];
- Os *Eight hop Test* e *Up-down hop Test* contribuem para a recuperação em doenças relacionadas com membros inferiores e alterações no equilíbrio [37];
- Os *Side hop Test* e *Single hop Test* auxiliam na recuperação de doenças relacionadas com o sistema neurológico [37];
- O *Chair Stand Test* auxilia na recuperação de lesões dos membros inferiores, alterações de equilíbrio e patologias neurológicas [38], [39];
- O *Arm Curl Test* contribui para a recuperação de lesões nos membros superiores e patologias neurológicas [37];
- O *Chair Sit and Reach Test* auxilia a recuperação de patologias nos membros inferiores e/ou superiores, bem como patologias neurológicas [37];
- O *Timed-Up and Go Test* ajuda na recuperação de patologias relacionadas com o equilíbrio, patologias do foro neurológico, patologias do foro degenerativo, lesões dos membros inferiores e doença venosa crónica [40]–[44]. O *Timed-Up and Go Test* apresenta-se como a base de estudo desta dissertação. É um teste de fisioterapia constituído por seis fases, onde o individuo se encontra sentado numa cadeira, levanta-se, caminha três metros em frente, inverte a marcha, caminha três metros na direção contrária e volta a sentar-se na cadeira [40]–[44].

O âmbito desta dissertação consiste na implementação de um método automático para a análise das diferentes variáveis recolhidas durante a realização do *Timed-Up and Go Test* usando de sensores de baixo-custo e sensores de dispositivos móveis. Estes sensores são utilizados para aquisição de dados para posterior cálculo das diferentes características dos sinais para identificar movimentos irregulares durante o teste com recurso a métodos estatísticos. No final, são usados métodos de inteligência artificial para a possível identificação das doenças de forma automática.

Descrição do problema e Objetivos desta dissertação

Atualmente, a medição da performance e resultados do *Timed-Up and Go Test* é difícil e necessita a utilização de vários instrumentos. Dada a existência de diversos equipamentos que permitem a medição automática dos resultados, *i.e.*, sensores e dispositivos móveis, esta dissertação pretende instrumentalizar a realização do *Timed-Up and Go Test* em indivíduos idosos. A instrumentação deste tipo de teste apresenta-se como um desafio para aumentar a eficácia nos diagnósticos e estabelecer padrões de doenças para auxiliar os profissionais de saúde no seu tratamento.

Os sensores incluídos nos dispositivos móveis permitem a deteção de movimentos pela identificação de padrões com os dados dos mesmos. Estas potencialidades fizeram surgir oportunidades para criar métodos mais precisos para a deteção de doenças recorrendo a dispositivos de baixo-custo, abrindo um leque de estudos possível que serviu de base a esta dissertação.

Dada a facilidade de desenvolvimento de aplicações móveis que permitem a interação de diversos sensores para a deteção de movimentos, as mesmas podem ser utilizadas em benefício dos profissionais de saúde para o auxílio do diagnóstico e registo de recuperação do indivíduo. É cada vez mais frequente o desenvolvimento de soluções de cooperação entre os profissionais da tecnologia e os profissionais de saúde, sendo que existem diversos estudos que relacionam a fisioterapia e os sensores disponíveis em dispositivos móveis.

O objetivo principal desta dissertação consiste na recolha e análise de dados provenientes de diferentes tipos de sensores para a monitorização do *Timed-Up and Go Test*, permitindo a identificação de padrões de indivíduos e/ou doenças.

Tal como qualquer trabalho, esta dissertação tem objetivos mais específicos que detalham o objetivo principal. Assim, os objetivos específicos desta dissertação são:

1. Estudo do estado da arte, combinando o uso dos sensores embutidos em dispositivos móveis e a análise dos resultados do *Timed-Up and Go Test*, para identificar os métodos e características utilizados para a análise dos resultados do teste;
2. Estudo do estado da arte que relaciona a identificação de doenças com sensores inerciais de forma a possibilitar a criação de padrões e ajudar no diagnóstico de diferentes doenças;
3. Proposta de modelo conceptual da análise do *Timed-Up and Go Test* de modo a realizar o mesmo com idosos institucionalizados da região;
4. Desenvolvimento de uma aplicação móvel para aquisição dos dados que combine a aquisição dos dados dos sensores de dispositivos móveis e dois

BITalinos [45] com sensores de Eletroencefalografia, Eletrocardiografia e de pressão;
5. Análise dos dados recolhidos e extração das diferentes características dos sinais recolhidos;
6. Processamento dos dados estatisticamente e com redes neuronais artificiais de forma a identificar padrões de doenças ou padrões entre indivíduos.

Principais Contribuições

Esta secção descreve resumidamente as principais contribuições científicas do trabalho de pesquisa apresentado nesta dissertação as quais resultaram em publicações científicas em conferências e revistas internacionais.

A primeira contribuição desta dissertação consiste na análise do estado da arte relativo aos estudos publicados em literatura que são baseados no *Timed-Up and Go Test* e o uso dos sensores inerciais presentes nos dispositivos móveis para o cálculo das diferentes características dos sinais dos sensores e, consequentemente, obtenção dos resultados do teste [46].

A segunda contribuição desta dissertação apresenta o estudo do estado de arte com o objetivo de demonstrar a capacidade dos sensores presentes em dispositivos móveis para a deteção de determinadas doenças relacionadas com o movimento, sistema neurológico e sistema cardíaco [47].

A terceira contribuição desta dissertação consiste na apresentação do modelo concetual para implementação do sistema experimental para a análise de resultados obtidos a partir do *Timed-Up and Go Test*, apresentando o desenho do sistema e o posicionamento dos sensores para a realização do trabalho experimental [30].

A quarta contribuição desta dissertação consiste na apresentação e análise estatística dos resultados do trabalho experimental com recurso ao acelerómetro e magnetómetro do dispositivo móvel, e ao sensor de pressão ligado ao dispositivo BITalino colocado na cadeira, apresentando as caraterísticas da população envolvida nas experiências, limitações e condicionantes do cálculo dos dados [48].

A quinta contribuição desta dissertação consiste na apresentação e análise estatística dos resultados do trabalho experimental com recurso aos sensores de Eletrocardiografia e Eletroencefalografia para detetar as suas variações no decorrer do teste, apresentando as caraterísticas da população envolvida nas experiências, limitações e condicionantes do cálculo dos dados [49].

Por fim, a sexta e última contribuição consiste na utilização de algoritmos de inteligência artificial para a identificação automática de idade e doenças da população durante a realização do *Timed-Up and Go Test* [50].

Estado da arte

Esta dissertação de mestrado iniciou com a pesquisa do estado da arte relativa aos diversos conceitos, tais como a relação da realização do *Timed-Up and Go Test* com os sensores embutidos em dispositivos móveis, tendo-se de seguida analisado a relação entre as doenças identificadas e os sensores inerciais usados.

Revisão sistemática da utilização de dispositivos móveis para o *Timed-Up and Go Test*

Os idosos fazem parte de um dos grupos essenciais onde o avanço da tecnologia pode beneficiar a qualidade de vida [26], [51]–[53], sendo que cerca de 9% da população mundial tem 65 anos ou mais [54]–[56]. Nos países desenvolvidos, como é o caso de Portugal, a esperança média de vida está acima de 70 anos, podendo estes sistemas ter uma maior dispersão e utilização [56]. Esta população merece especial atenção, pois tem aumentado drasticamente o número de idosos, estimando-se que, em 2050, o número de idosos atinja os 2 biliões de indivíduos com mais de 60 anos [57], [58]. Contudo, a tecnologia traz inúmeras opções para a melhoria das condições de saúde desta população [59], [60], sendo que o número de pesquisas nesta área tem vindo a aumentar com o passar dos anos [3], [4].

De acordo com a literatura, os idosos foram questionados sobre a utilização de dispositivos móveis para estes fins, referindo que apenas usam os telemóveis para situações de emergência, tais como chamadas de voz, sendo que minoritariamente enviam mensagens de texto e realizam chamadas de vídeo [51], [61]. Atualmente, os dispositivos móveis têm um alto poder de processamento, vários sensores e várias formas de ligação a outros dispositivos, *i.e.* Bluetooth, Wi-Fi, entre outros [62]. Estes dispositivos incorporam vários sensores, *e.g.* acelerómetro, magnetómetro e giroscópio, que dada a sua natureza podem ser utilizados para apoiar vários procedimentos de avaliação clínica, identificação e auxílio das atividades de vida diária, e deteção de situações de risco, *i.e.* quedas [9], [12]–[14], [63]–[67]. Assim, verifica-se que a cooperação entre os profissionais de saúde e profissionais da tecnologia é benéfica para o desenvolvimento de métodos eficientes [1].

O *Timed-Up and Go Test* é um método clínico que permite a avaliação da funcionalidade dos membros inferiores, mobilidade e risco de quedas [68]. Durante este teste, a pessoa realiza as seguintes ações: levanta-se da cadeira, caminha 3 metros, inverte o sentido da marcha, caminha 3 metros na direção inversa e senta-se na cadeira. A duração típica deste teste é de, no máximo, 12 segundos. Este teste tem tido algumas evoluções com a criação de diferentes variantes, tais como *Timed-Up and Go test* normal, *Extended Timed-Up and Go test*, *Smart Insole Timed-Up and Go test*, e *Instrumented Timed-Up and Go test* [69]–[73].

As questões de pesquisa desta revisão de literatura centram-se na forma como os sensores inerciais de baixo-custo podem ser utilizados para melhorar a monitorização do teste, nos métodos de análise que podem ser implementados com dispositivos móveis, e na prevenção do risco de quedas.

Assim, foi efetuada uma pesquisa em várias bases de dados, tais como IEEE Xplore, ACM Digital Library, BMC e PubMed, pesquisando artigos científicos relativos às variantes do *Timed-Up and Go test*, que implementem soluções com base nos sensores disponíveis em dispositivos móveis, que tenham sido publicados entre 2010 e 2018 e que definam corretamente a população em estudo.

Os diferentes estudos foram analisados tenho em conta o ano de publicação, a população em estudo, o objetivo do estudo, os dispositivos utilizados, os sensores utilizados, a implementação realizada e as doenças que estavam presentes na população.

Foram analisados 28 estudos. Maioritariamente, os estudos analisados eram recentes, tendo 46% deles sido realizados entre 2017 e 2018, existindo uma grande dispersão nos restantes anos. Em relação ao tipo de dispositivo utilizado, verificou-se que 71% utilizou o smartphone e 29% utilizaram outros dispositivos móveis. Por sua vez, relativamente aos sensores, o acelerómetro é utilizado em 97% dos estudos, o giroscópio é utilizado em 68% dos estudos e o magnetómetro é utilizado em 25% dos estudos. Somente 29% dos estudos apresentam a precisão do estudo. Em relação às doenças presentes na população estudada, 18% analisaram indivíduos com Parkinson, 14% com síndrome de fragilidade, 50% por cento dos estudos foram realizados em pessoas saudáveis e 18% com outros tipos de doenças.

Na análise dos dados foram extraídas as diferentes características do sinal dos diferentes sensores e categorizadas em cinco categorias, são elas: quantitativa, quantitativa + estatística, equilíbrio, transições de estado e estatística de dados não tratados. As características mais utilizadas na literatura foram duração do teste, número de passos, tamanho do passo, aceleração, velocidade angular máxima, velocidade da marcha, média dos dados em bruto, desvio padrão dos dados em bruto, entre outros.

Durante o estudo, os diversos autores identificaram diversos problemas, tais como movimentos ou trajetórias involuntárias, efeitos de medicamentos ou deficiências, o facto de a distância reduzida do teste poder afetar a fiabilidade dos resultados, e a medição e cálculo das características estar dependente de condições pessoais ou ambientais.

Na grande maioria dos estudos, o principal objetivo consistia no cálculo do risco de quedas, sendo este teste importante para pessoas debilitadas ou com dificuldades físicas.

Revisão sistemática da Identificação de Doenças com base no uso de Sensores Inerciais

Atualmente, 9% da população mundial tem mais de 64 anos e 10% dessas pessoas terão deficiências [54], [56]. Este facto leva a impactos relevantes na economia e na saúde, nomeadamente nos cuidados de saúde primários [57], [58]. Portugal não é exceção e está incluído nos 5 países com mais idosos em todo o mundo, mas está no topo da lista de países com menos nascimentos na Europa [74], [75]. Dada a desproporcionalidade entre os nascimentos e o envelhecimento da população, é cada vez mais importante o desenvolvimento de novas estratégias que recorram à tecnologia pra promover a saúde e o bem-estar dos cidadãos [76].

Nesta revisão de literatura, as questões de pesquisa centram-se no número de pessoas envolvidas nos estudos com o uso de sensores inerciais, nas doenças detetadas com os dados desses sensores, e nos métodos que são utilizados para essa deteção.

A pesquisa foi efetuada nas bases de dados IEEE Xplore, ACM Digital Library, ScienceDirect, MEDLINE e PubMed, identificando estudos que realizam o reconhecimento de doenças com recurso usando sensores inerciais, que tenham sido publicados entre 2008 e 2020 e que indicavam o número de participantes envolvidos no estudo.

Foram encontrados 13 estudos, os quais foram analisados tendo em conta o ano de publicação, a população em estudo, o objetivo do estudo, os sensores utilizados, as doenças detetadas e a precisão de cada estudo.

Os estudos analisados foram publicados de forma dispersa entre os anos de 2008 e 2018, sendo que o maior número de estudos foi publicado em 2014. Em média, os diferentes estudos consideraram os dados adquiridos por um número diferente de pessoas entre 5 e 85 pessoas, onde o maior número de indivíduos aumenta a confiabilidade do estudo. A análise dos diversos estudos permitiu verificar que 31% utilizaram o giroscópio, 8% utilizaram o magnetómetro, 8% utilizaram o recetor de GPS, 8% utilizaram o sensor de eletromiografia e 8% utilizaram o sensor de eletrocardiografia. O sensor mais utilizado foi o acelerómetro em 85% dos estudos. Em relação às doenças, 54% dos estudos identificam a doença de Parkinson. Os restantes distúrbios são identificados apenas em um estudo cada e são radiculopatia lombar, fraqueza, epilepsia, doença bipolar, andadores idiopáticos, esclerose múltipla, arritmia e apneia do sono.

Os métodos de inteligência artificial mais implementados para análise dos dados recolhidos são *Random Forest*, *Support Vector Machine* (SVM), *Naive Bayes*, *k-Nearest Neighbor* (kNN), *Decision Tree-based method* (PART), C4.5 *Decision Tree* e *K-means*.

O acelerómetro é usado para deteção de diversas doenças com maior prevalência na doença de Parkinson pela sua capacidade de identificação das derivações angulares que os indivíduos com este tipo de doença apresentam em movimento.

A análise destes trabalhos permitiu identificar as potencialidades do uso de sensores inerciais na deteção de doenças, as potencialidades do conceito mHealth, as doenças mais detetadas com este tipo de sensores e quais os métodos de inteligência artificial usados pelos investigadores para aumentar a inteligência dos sistemas apresentados para a sua deteção.

Proposta de Sistema para a Análise dos Resultados do *Timed-Up and Go Test*

Após a revisão de literatura relativa aos diversos conceitos, a arquitetura do método de análise proposto para estimação automática dos resultados do *Timed-Up and Go Test*, e respetiva identificação de doenças relacionadas, foi definida e apresentada, incluindo os diversos conceitos abordados na revisão de literatura.

Medição automática dos resultados do *Timed-Up and Go Test* utilizando dispositivos móveis

O método proposto tem por objetivo a investigação centrada na instrumentalização do *Timed-Up and Go Test* com base em sensores embebidos num dispositivo móvel comum e a utilização de sensores de Eletroencefalografia e Eletrocardiografia ligados a um dispositivo BITalino [45] aplicado a idosos.

Assim, o problema abordado consiste na utilização de dispositivos de baixo custo para facilitar e aumentar a precisão dos diagnósticos com base no *Timed-Up and Go Test* utilizando sensores inerciais como principal mecanismo de medição. Este problema é ao mesmo tempo uma oportunidade que assenta no facto de a população idosa estar a aumentar o seu número quando comparado com a população jovem. A utilização de métodos não invasivos para medições dos parâmetros físicos e fisiológicos desta população, pode aumentar a sua aceitação [77], [78], facilitando a promoção da qualidade de vida da população [79], [80].

A aquisição de dados centra-se na execução do *Timed-Up and Go Test* com um telemóvel à cintura, um sensor de pressão posicionado na cadeira, e conectado a um BITalino, e os sensores de Eletroencefalografia e Eletrocardiografia, posicionados no individuo, ligados a outro dispositivo BITalino. Do telemóvel são capturados os sinais do acelerómetro e do magnetómetro com recurso a uma aplicação móvel. A aplicação móvel agrega igualmente os dados dos dispositivos BITalino, guardando os todos os dados em ficheiros de texto, fazendo posteriormente o seu envio para a Cloud.

Como métodos de análise é proposta a extração de diferentes características como: tempo de reação, tempo do teste, tempo de ida, tempo de regresso, tempo de viragem, velocidade, força, potência, frequência cardíaca, variabilidade cardíaca, variabilidade da atividade cerebral, entre outros parâmetros.

No final, são implementados diversos métodos de análise estatística [81], [82] e métodos de inteligência artificial, tal como redes neuronais artificiais [83]–[86]. Verificou-se que a execução do teste tem diferentes condicionantes, tais como consumo de bateria, ligação entre os diferentes dispositivos, limitações da *Application Programming Interface* (API) do dispositivo BITalino [45] e necessidade de ligação à Internet para armazenamento dos dados na *Cloud*.

Resultados do Sistema para a Análise dos Resultados do *Timed-Up and Go Test*

Por fim, os detalhes da implementação do método para análise dos resultados do *Timed-Up and Go Test* foram apresentados, utilizando os diversos sensores disponíveis nos dispositivos móveis e sensores ligados ao dispositivo BITalino, sendo a análise dos dados efetuada com recurso a métodos estatísticos e de inteligência artificial.

Tecnologias de computação móvel para avaliação de saúde e mobilidade: Análise da Implementação do Timed-Up and Go Test com idosos

Cada vez mais, a população mundial está envelhecida devido a um decréscimo do número de nascimentos e a existência de cada vez mais idosos [87]–[90]. O aparecimento dos sensores em dispositivos utilizados diariamente possibilitou a criação de soluções adaptadas aos cuidados de saúde primários [91]. Outro dos fatores relevantes é o facto de a esperança média de vida ter aumentado, sendo que isso tornou importante a criação de soluções que melhorem a qualidade de vida [92].

Os diferentes sensores incluídos nos dispositivos móveis possibilitam a aquisição de parâmetros físicos e fisiológicos dos indivíduos, permitindo adaptar as soluções aos diferentes ambientes e condições de saúde dos idosos, sendo que alguns dos sensores mais presentes neste tipo de dispositivos são o acelerómetro e o magnetómetro. Estes sensores permitem analisar a marcha, entre outros parâmetros relativos a cada indivíduo [32], [93]–[96].

Assim, criou-se um método para a medição automática dos resultados do *Timed-Up and Go Test* com os sensores disponíveis num dispositivo móvel utilizado diariamente. Com estes dados será possível identificar diversos padrões de doenças presentes nos indivíduos e que direta ou indiretamente estejam relacionadas com o simples facto de andar. Para além disso, os dados recolhidos permitiram estabelecer comparações entre indivíduos de diferentes instituições, procedendo às análises por idade, instituição e diferentes doenças.

O estudo foi realizado com recurso a um dispositivo móvel com sistema operativo Android. Foi posicionado um sensor de pressão, ligado a um dispositivo BITalino [45], numa cadeira onde o idoso se senta antes de realizar o teste e o dispositivo móvel foi colocado numa bolsa à cintura do idoso. Os testes referentes às diferentes fases do *Timed-Up and Go Test* foram realizados com indivíduos entre os 60 e os 97 anos de diferentes instituições, extraindo os seguintes dados dos diferentes sensores:

- **Sensor de pressão**: Tempo de reação; Tempo total do teste;
- **Acelerómetro**: Tempo de reação; Tempo total do teste; Instante de viragem; Duração da viragem; Tempo de ida; Tempo de Retorno; média de aceleração de ida; média da aceleração de regresso; média da velocidade de ida; média da velocidade de regresso; média da força de ida; média da força de regresso; média da potência de ida; média da potência de regresso;
- **Magnetómetro**: Tempo total do teste; Instante de viragem segundo o eixo do z; Instante de viragem segundo o módulo da aceleração.

Os dados foram recolhidos com um dispositivo móvel com sistema operativo Android com uma taxa de recolha de dados de 1 kHz e uma precisão de 16 bits. Contudo, um dos maiores constrangimentos foi a necessidade de ligação à Internet para sincronização dos diferentes ficheiros capturados para a plataforma Firebase.

Outro problema estava relacionado com as falhas nas ligações Bluetooth entre os diferentes dispositivos, mas foi um dos pontos que foi contornado com regular verificação.

Para a realização do teste foram identificados vários requisitos, nomeadamente o individuo devia ter capacidade de caminhar e se levantar, necessidade de uma cadeira, necessidade de uma fita métrica para estabelecer o limite de 3 metros para a experiência, instrumentalização dos idosos e colocação do cinto com o dispositivo móvel. O estudo foi realizado por 40 idosos institucionalizados da região do Fundão (Portugal).

Os resultados do teste foram avaliados estatisticamente, analisando o cálculo do tempo de viragem pelo estudo do módulo da aceleração ou do eixo do z estimado com o magnetómetro. Assim, três análises comparativas foram realizadas com as diferentes recolhas, tais como por idade, por doença e por instituição.

De acordo com os resultados agrupados por idades (existiam 3 intervalos de idades), tendo em conta os valores recolhidos com o sensor de pressão, de 60 a 74 anos, o tempo de reação é, em media, de 7,175 segundos e o tempo total é, em media, 27,709 segundos, de 75 a 89 anos verificou-se, em média, 8,528 segundos para o tempo de reação e 40,881 segundos para o tempo total do teste, e em idosos com 90 ou mais anos de idade verificou-se, em médio, um tempo de reação de 8,153 segundos e o tempo total de 34,795 segundos.

Por sua vez, tendo em conta os valores recolhidos pelo magnetómetro, o momento de viragem utilizando o valor da aceleração é de 22,182 segundos para indivíduos entre os 60 e 74 anos, 17,64 segundos para indivíduos entre os 75 e 89 anos e 20,783 segundos em indivíduos com 90 ou mais anos, e o momento de viragem tendo em conta o valor absoluto do eixo do z é de 22,384 segundos para indivíduos entre os 60 e 74 anos, 23,27 segundos para indivíduos entre os 75 e 89 anos e 20,281 segundos em indivíduos com 90 ou mais anos. Finalmente, tendo em conta os dados do magnetómetro, em média, o tempo total do teste é 29,262 segundos para indivíduos entre os 60 e 74 anos, 36,288 segundos para indivíduos entre os 75 e 89 anos e 33,091 segundos em indivíduos com 90 ou mais anos.

No caso da análise por doenças, as mesmas foram distribuídas por dois grupos, sendo um deles relacionado com a mobilidade e o outro não. Não se identificaram diferenças no tempo total do teste relacionadas com as doenças. Contrariamente, o instante de viragem já se encontra diferenciado entre as doenças relacionadas com mobilidade ou não, mas a média é estatisticamente igual.

Os dados foram adquiridos com diferentes particularidades entre pessoas e instituições, sendo que proporcionaram a obtenção de resultados bastante diversificados e heterogéneos. As diversas limitações encontradas podem ser classificadas em 3 grupos: relacionadas com o estado físico dos indivíduos, o ambiente da experiência e as condições técnicas. Cada um dos grupos tem maior ou menor influência nos resultados, mas, no geral, os resultados obtidos foram satisfatórios.

Estudo experimental para a identificação de doenças relacionadas ao ECG e EEG durante o *Timed-Up and Go Test*

Hoje em dia, os dispositivos móveis incorporam diferentes sensores que podem ser utilizados para a medição de diversos parâmetros físicos e fisiológicos durante a realização do *Timed-Up and Go Test* [97].

O *Timed-Up and Go Test* possibilita a identificação de vários problemas de saúde, tais como equilíbrio, mobilidade, risco de queda, doença de Parkinson, esclerose lateral amiotrófica e outras patologias ortopédicas, cardiovasculares e cerebrais [44], [98]–[102]. Contudo, a utilização dos sensores de Eletroencefalografia e Eletrocardiografia em conjunto com a realização do *Timed-Up and Go Test* possibilita também a identificação de problemas associados aos sistemas cardíaco e nervoso [103]–[107].

Um sensor de Eletrocardiografia e um sensor de Eletroencefalografia foram conectados a um dispositivo BITalino [45]. O sensor de Eletrocardiografia deteta a duração e a variação no tamanho das ondas de Eletrocardiografia que podem ser usadas para identificar anormalidades da frequência cardíaca. Por sua vez, o sensor de Eletroencefalografia é usado para a captura da atividade cerebral e está posicionado em uma configuração bipolar com dois elétrodos de medição para a deteção de sinais elétricos.

Os dados recolhidos foram analisados estatisticamente de modo a identificar correlações entre as características da população, e doenças presentes na mesma, com os dados dos sensores de Eletrocardiografia e Eletroencefalografia.

A população analisada foi a mesma do estudo anterior e que tem várias doenças, tais como Arritmia cardíaca, Insuficiência cardíaca, Diabetes Melitos tipo II, Depressão, Síndrome de vertigem, Osteoartrite, Osteoporose, Hiperuricemia, Gonartrose bilateral e Doença pulmonar obstrutiva crónica.

Os dados de Eletrocardiografia e Eletroencefalografia foram processados, procedendo-se à extração de diferentes características. São elas:

- Eletrocardiograma: Variabilidade da frequência cardíaca; frequência cardíaca; média da amplitude do intervalo QRS; média da amplitude do intervalo R-R; média da amplitude do intervalo R-S;

- Eletroencefalograma: frequência dos picos do sinal; variabilidade dos picos do sinal.

Foram realizadas diferentes análises tendo em conta a posição dos sensores, doenças presentes população em estudo, idade e condições do teste. Para a análise dos resultados, foram realizadas estatísticas descritivas, testes de normalidade e deteção de *outliers*. Além disso, foi realizada uma comparação estatística entre eles, analisando e comparando os resultados pelas médias de cada instituição, pessoa, idade e doenças da saúde.

Assim, na generalidade, verificou-se que:

- a hipertensão arterial pode ser identificada quando a amplitude do intervalo QRS for menor que 700 ms;
- A arritmia ou insuficiência cardíaca é identificada pelas irregularidades do batimento cardíaco com a existência de grande variabilidade;
- A doença de Parkinson e a gonartrose bilateral podem ser identificadas por uma elevada amplitude do intervalo QRS e uma amplitude do intervalo R-R superior a 2000 ms.

Não há doenças relacionadas ao Eletroencefalografia relatadas pela população. No entanto, verifica-se que a variabilidade da atividade cerebral aumenta com a idade. Além disso, a atividade cerebral é menor em pessoas com doença de Parkinson.

Por fim, é verificado que a população é muito heterogénea, levando a valores muito diferentes. Também as condições de realização do teste devem ser melhoradas para a obtenção de melhores resultados. Contudo, foi possível estabelecer um termo de comparação com a literatura, verificando que os valores estão alinhados.

Estudo exploratório sobre técnicas de aprendizagem máquina com dados de ECG e EEG

Cada vez mais têm surgido métodos não evasivos de adquirir sinais de Eletrocardiografia e Eletroencefalografia, permitindo o desenvolvimento de sistemas de baixo custo relacionados com a área da medicina com o uso da tecnologia [108], [109]. Estes sistemas permitem uma primeira fase de diagnóstico sem necessidade de intervenção médica, mas existem diversos desafios relacionados com o posicionamento dos sensores e/ou dispositivos móveis [8], [110], [111]. Diferentes estudos têm sido realizados com recurso a técnicas de visão computacional e aprendizagem máquina, analisando diversos parâmetros físicos, fisiológicos e biológicos em idosos [51], [52], [112]–[114].

Assim, pretendeu-se implementar redes neuronais artificiais para identificar padrões e identificar as diferentes doenças presentes no estudo realizado com recurso ao *Timed-Up and Go Test* [30], [115]. O teste foi realizado com idosos institucionalizados dos concelhos do Fundão e a Covilhã, implementando métodos para a extrapolação das idades, instituições, doenças e grupos de doenças.

Inicialmente, foram extraídas as diferentes características dos sinais por cada execução do teste, tais como frequência cardíaca, variabilidade da frequência cardíaca, média da amplitude do intervalo QRS, média da amplitude do intervalo R-R, média da amplitude do intervalo R-S, frequência dos picos do sinal de Eletroencefalografia e variabilidade dos picos do sinal de Eletroencefalografia.

Após a classificação manual da amostra tendo em conta as informações clínicas dos idosos que realizaram o teste, foi implementado e validado o método de redes neuronais com o *software* WEKA [116]. Os parâmetros que foram definidos são os seguintes:

- Taxa de aprendizagem: 0,3;
- Momento: 0,2;
- Normalização de atributos e classes;
- Valor da semente: 0;
- Tempo de treino: 500ms;
- Limite de validação: 20.

Após a validação verificou-se que que os indivíduos poderiam ser reconhecidos pelas instituições, onde apenas os indivíduos do *Centro Comunitário das Lameiras* não foram identificados corretamente. Relativamente às idades, somente os indivíduos com 74, 85 e 86 anos não foram reconhecidas corretamente.

Quanto ao reconhecimento das doenças, elas não foram identificadas corretamente, pois a amostra era composta por um pequeno número de indivíduos. No entanto, as doenças foram categorizadas, verificando-se que as doenças cardíacas eram corretamente identificadas.

Principais Conclusões

O foco desta dissertação está relacionado com a instrumentalização do *Timed-Up and Go Test* aplicado à fisioterapia com recurso a sensores de dispositivos móveis, *e.g.*, acelerómetro, magnetómetro e giroscópio, e sensores de pressão, Eletrocardiografia e Eletroencefalografia ligados a dispositivos BITalino. Foi proposta a arquitetura do sistema para aquisição dos dados e foi implementada uma aplicação para aquisição dos diversos sinais provenientes dos sensores. As diferentes características dos sinais dos diferentes sensores foram analisadas para extrapolar diferentes conclusões sobre a realização do teste.

Assim, durante esta dissertação foram adquiridos sinais usando vários sensores durante a realização do *Timed-Up and Go Test*, aplicando análise estatística e métodos de inteligência artificial para a identificação das diferentes fases do teste e validação da execução do mesmo.

Esta dissertação foi executada em diferentes fases, em que, inicialmente, foi realizado o estudo do estado da arte sobre a instrumentação do *Timed-Up and Go Test*. Esta análise consistiu na análise das características, métodos e sensores previamente utilizados na literatura. Adicionalmente, foram analisados diversos estudos na deteção de doenças relacionadas com o movimento.

Foi proposta a arquitetura do sistema com diferentes sensores e dispositivos, definindo o *Timed-Up and Go Test* e o posicionamento dos sensores durante o mesmo.

De seguida, o sistema foi implementado e diversos testes foram realizados, procedendo-se ao cálculo das características do sinal dos diferentes sensores, analisando as diferentes limitações previamente apresentadas.

Assim, com o acelerómetro, magnetómetro e sensor de pressão foram identificadas as seguintes características: tempo de reação, tempo do final da aquisição de dados, tempo total do teste, instante de viragem, tempo de viragem, tempo de ida, tempo de regresso, média da aceleração de ida e de regresso, média da velocidade de ida e de regresso, média da força de ida e de regresso, e média da potência de ida e de regresso. Por sua vez, com os sensores de Eletrocardiografia e Eletroencefalografia foram identificadas as seguintes características: Variabilidade da frequência cardíaca, frequência cardíaca, média da amplitude do intervalo QRS, média da amplitude do intervalo R-R, média da amplitude do intervalo R-S, frequência dos picos do sinal de Eletroencefalografia e variabilidade dos picos do sinal de Eletroencefalografia.

Para a análise dos dados foram utilizados diferentes métodos estatísticos, como a ANOVA, o coeficiente de correlação de Pearson, testes comparativos, entre outros, e métodos de inteligência artificial, tal como redes neuronais artificiais. Contudo, estas experiências revelaram algumas limitações associadas à capacidade da bateria, armazenamento limitado, ligação à Internet para o envio dos ficheiros para o servidor e ligação Bluetooth para a aquisição dos dados provenientes dos dispositivos BITalino.

Esta dissertação terminou com a implementação preliminar de métodos de inteligência artificial para a deteção de padrões de doenças e relacionando as diferentes variáveis de Eletrocardiografia e Eletroencefalografia. Assim, foi possível verificar que é possível detetar e identificar doenças e idade com diferentes características do sinal.

Direções Para Trabalho Futuro

Os resultados obtidos nesta dissertação são promissores. No entanto, é importante aumentar o número de testes, devendo ser realizadas experiências com uma população mais diversificada de diferentes regiões do país ou até do mundo. Para esta análise devem ser calculadas diferentes características do sinal dos diferentes sensores, tentando reduzir os efeitos da gravidade terreste.

Em continuação do trabalho iniciado nesta dissertação, outros métodos de inteligência artificial devem ser implementados em acréscimo às redes neuronais artificiais, mais como *Deep Learning, Adaboost, Support Vector Machine (SVM), Decision Tree*, entre outros. Assim, poder-se-á obter melhores resultados na deteção de doenças e identificação dos parâmetros do *Timed-Up and Go test*.

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Abstract

The recent technological advances and the growing use of mobile devices have allowed the emergence of several studies in different areas of human life. These devices are equipped with various sensors that enable the acquisition of different physical and physiological parameters from different individuals. The development of intelligent systems with sensors is one of the topics addressed by Ambient Assisted Living (AAL) systems. Several areas of medicine have benefited from these advances providing long distance clinical healthcare. Still, the focus of this dissertation is one of the functional tests focused on physiotherapy, the Timed-Up and Go test.

Mobile devices present themselves with more and more solutions, functionalities and processing capacity. The presence of sensors in mobile devices, such as the accelerometer, magnetometer and gyroscope, allows the acquisition of signals related to physical activity and human movement. Also, as these devices include the possibility of connecting via Bluetooth, other sensors can be used in conjunction with the sensors included in the mobile device. For this dissertation, the BITalino device was used to connect sensors such as the pressure sensor, the Electrocardiography sensor and the Electroencephalography sensors.

The scope of this dissertation consists of the statistical analysis and with the artificial intelligence of the data collected during the execution of the Timed-Up and Go test using several sensors. For this purpose, a mobile application was developed that allows the acquisition of data from several sensors during the execution of the test with institutionalized older adults.

The Timed-Up and Go test is defined as a test widely used by physiotherapists in the recovery of injuries and consists of 5 phases, where the individual is sitting in a chair, walks three meters, reverses the gait, walks three meters and comes back to sit in the chair.

The main focus of this dissertation is the creation of a method for analyzing the results of the Timed-Up and Go test using the accelerometer and magnetometer of the mobile device and a pressure sensor positioned on the chair using the BITalino device. At the same time, signals from Electrocardiography and Electroencephalography sensors connected to another BITalino device were collected for the analysis of different health problems. Thus, statistical and artificial intelligence methods were implemented for the study of these sensors using the experimental procedure initially performed.

Initially, the literature review related to the Timed-Up and Go test and the use of sensors was performed, and the literature review ended with the identification of diseases that could be identified using inertial sensors. Then, the architecture proposal to be used for data collection was presented, taking into account the sensors mentioned above. The data available in this study were collected by 40

institutionalized elderly people from the Fundão municipality (Portugal), instrumented with a mobile device and a BITalino device, as well as the other sensors. Finally, the collected data was then analyzed, which was divided into three stages, starting with the analysis of the accelerometer, magnetometer and pressure sensor to identify the parameters of the Timed-Up and Go test, using statistical methods for data analysis. In the second stage, statistical methods were implemented to correlate the diseases that could be detected by Electrocardiography and Electroencephalography sensors. Finally, in the third stage, artificial intelligence methods were applied, *i.e.*, artificial neural networks, to relate cardiac and nervous diseases with the data of different individuals to assess their characteristics.

As a future work, the results presented in this dissertation serve as a path to the creation of a low-cost and access system for all citizens, which allows for the timelier detection of specific disorders and can assist health professionals in the diagnosis and disease treatment.

Keywords

Timed-Up and Go test, sensors, mobile device, physical teraphy, data processing.

Contents

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Acronyms

AAL	Ambient Assisted Living
AAM	Active Appearance Model
ACQUA	Acquisition Cost-Aware Query Adaptation
ADL	Activities of Daily Living
ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
BSN	Body Sensor Network
BSS	Blind Source Separation
DNN	Deep Neural Networks
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
FFT	Fast Fourier Transform
FOG	Freezing of Gait
GPRS	General Packet Radio Service
GPS	Global Positioning System
HSDPA	High-Speed Downlink Packet Access
IDE	Integrated Development Environment
IMU	Inertial Measurement Unit
IQR	Interquartile Range
ITUG	Instrumented Timed-Up and Go
ITW	Idiopathic Toe-Walking
kNN	k-Nearest Neighbors
LIME	Local Interpretable Model-agnostic Explanations
NFC	Near-field Communication
PART	Decision Tree-based Method
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
PWM	Pulse Wave Modulation
RMS	Root Mean Square
RMSE	Root Mean Square Error
SHAP	Shapley Additive Explanations
SITUG	Smart Insole Timed-Up and Go

SMA	Signal Magnitude Area
SVM	Support Vector Machine
TUG	Timed-Up and Go
UART	Universal Asynchronous Receiver-Transmitter
UPDRS	Unified Parkinson’s Disease Rating Scale
WEKA	Waikato Environment for Knowledge Analysis

1. Introduction

This master's dissertation addresses the problem of implementing an automatic analysis method of the Timed-Up and Go Test, using the sensors available on the mobile device, such as the accelerometer, magnetometer and the gyroscope, and other sensors connected to BITalino devices, such as the pressure sensor, electrocardiogram and electroencephalogram.

As a result, this dissertation proposes a method that combines the use of the proposed sensors to analyze the execution parameters of the Timed-Up and Go test and the related diseases. The focus, scope and research objectives of this dissertation are presented in this chapter, followed by the main contributions and organization of the dissertation.

1.1. Focus and Scope Dissertation

The growing technological development has created new research opportunities in the most diverse areas of human life, where it is heterogeneous with several points in common [1]–[4]. The emergence and development of systems with sensors and the increasing capabilities of the related devices have improved the scope and implementation of such studies [5]–[11].

The rapid and increasing development in the mobile devices market, namely smartphones, smartwatches, and tablets, has led to the development of mobile devices with several functionalities, including higher power processing, memory, sensors, and battery capabilities [12]–[14]. The sensors included in these devices are mainly the accelerometer, magnetometer, gyroscope, and Global Positioning System (GPS) receiver, among others. This presents an excellent opportunity to develop diverse solutions in different areas of human life [15]–[20]. Thus, because of their size and the facility of application development capabilities, the sensors available in off-the-shelf mobile devices are sensors with large and countless capacities that have led to a new number of new research opportunities [6], [8], [21], [22].

Sensors are useful in several areas, including the acquisition of several physical and physiological parameters [5], [9], [19], [23]–[26]. For instance, physiotherapy is one of the areas in which they can be useful, contributing to a more accurate identification of the results in several tests. The different measurements may be performed with the acquisition of data from the sensors available in the off-the-shelf mobile devices or from other sensors. These mobile devices also allow the different measurements to be carried out locally can send the data over a network connection for further processing in a remote server. In any case, the main goal is the automatic measurement of the results and situations related to physical activities or movements [27]–[31].

Different types of measurements can be performed with the sensors available in the off-the-shelf mobile devices. As the focus of this dissertation of related to the physical therapy subject. Thus, some of the most common physical therapy tests that can be implemented with sensors are as follows:

- The Heel-Rise test is intended for pathologies related to chronic venous disease, dysfunctions in the leg around the twins, ruptures or tendonitis in the Achilles tendon, sports injuries, and neurological and/or degenerative pathologies [32], [33];
- The Functional Reach test is intended for the recovery of pathologies related to the injuries of the upper limbs, neurological and/or degenerative pathologies and sports injuries [21], [34];
- The Ten Meter Walk test seeks to help in the recovery of the related pathologies, such as balance changes, neurological and/or degenerative pathologies, lower limb injuries and chronic venous disease [35], [36];
- The Eight Hop test and the Up-down Hop test contribute to the recovery from lower limb-related diseases and changes in balance [37];
- The Side Hop test and the Single Hop test assist in the recovery of diseases related to the neurological system [37];
- The Chair Stand test assists in the recovery of lower limb injuries, balance changes and neurological pathologies [38], [39];
- The Arm Curl test contributes to the recovery of injuries in the upper limbs and neurological pathologies [37];
- The Chair Sit and Reach test assists in the recovery of pathologies in the lower and/or upper limbs, as well as neurological pathologies [37];
- Finally, the Timed-Up and Go test helps in the recovery of pathologies related to balance, neurological pathologies, degenerative pathologies, lower limb injuries and chronic venous disease [40]–[44]. The Timed-Up and Go test presents itself as the basis for the study reported in this dissertation. It is a physical test consisting of six phases, where the individual is seated in a chair, gets up, walks three meters in front, reverses the gait, walks three meters in the opposite direction and sits back in the chair [40]–[44].

The scope of this dissertation included the implementation of an automatic method for the analysis of the different variables present in the data acquired from the different sensors during the performance of the Timed-Up and Go test by using low-cost sensors and the sensors available in off-the-shelf mobile devices. These sensors were used to acquire data for a later calculation of the different features of the signals to identify irregular movements during the test with statistical methods. At the end, artificial intelligence methods were used for the automatic identification of pattern from the different diseases.

1.2. Description of the problem and objectives of this dissertation

Currently, the measurement of the performance and results of the Timed-Up and Go test is difficult and requires the use of several instruments. Given the existence of various types of equipment that allow the automatic measurement of results, *i.e.*, sensors and mobile devices, this dissertation intends to instrumentalize the performance of the Timed-Up and Go test in older adults. The instrumentalization of such a test presents itself as a challenge to increase the effectiveness of the diagnoses and to establish disease patterns to assist health professionals in the treatment of different diseases.

The sensors included in the off-the-shelf mobile devices allow the detection of movements by identifying patterns with the data acquired. These potentialities have led to opportunities to create more accurate methods for the detection of diseases by using low-cost devices, opening a range of possible studies that served as the basis for this dissertation.

Given the ease of development of mobile applications that allow the interaction of several sensors for the detection of movements, these applications can be used for the benefit of health professionals to assist in the diagnosis and recording of an individual's recovery. It is increasingly common to develop collaborative solutions between technology and healthcare professionals, and several studies related to physical therapy and sensors available on mobile devices have been conducted thus far.

The main objective of this dissertation was to collect and analyze data from different types of sensors, including the accelerometer, the magnetometer, the pressure sensor, the Electroencephalography sensor, and the Electrocardiography sensor, to monitor the performance of the Timed-Up and Go test, allowing the creation of patterns of individuals and/or diseases. The inclusion of the last two sensors was related to the existence of different diseases related to cardiology and neurology in the older adults and might affect the performance of the test.

Therefore, this dissertation had more specific objectives that refined the main objective. These specific objectives of this dissertation were as follows:

1. Study the state-of-the-art technology that combines the use of sensors embedded in mobile devices and analyzes the results of the Timed-Up and Go test to identify the methods and characteristics used for the development of the test results;
2. Study the state-of-the-art technology related to the identification of diseases with inertial sensors to enable the creation of patterns and help in the diagnosis of different diseases;

3. Propose a conceptual model for the analysis of the Timed-Up and Go test for its implementation with the institutionalized older adults from Fundão and Covilhã municipalities (Portugal);
4. Develop a mobile application for data acquisition that combines the acquisition of data from the sensors of mobile devices and two BITalino devices [45] with Electroencephalography, Electrocardiography and pressure sensors;
5. Analyse the acquired data and extract the different characteristics of the acquired signals;
6. Process the acquired data with statistical methods to combine the results from the different sensors and measure the different parameters of the test;
7. Analyze the acquired data with artificial neural networks and statistical methods for the identification of patterns by age, institution, diseases, and classification of diseases.

1.3. Main Contributions

This section briefly describes the main scientific contributions resulting from the research work presented in this dissertation. The first contribution of this dissertation consists of analyzing the state-of-the-art technology regarding studies published in the literature that are based on the Timed-Up and Go test and the use of inertial sensors present in mobile devices for the calculation of the different characteristics of the sensor signals and, consequently, obtaining the test results [46].

The second contribution of this dissertation presents the study on the state-of-the-art technology to demonstrate the capacity of sensors present in mobile devices for the detection of certain diseases related to movement, neurological and cardiac systems [47].

The third contribution of this dissertation consists of the presentation of the conceptual model for the implementation of the experimental system to analyze the results obtained from the Timed-Up and Go Test [30].

The fourth contribution of this dissertation consists of the presentation and the statistical analysis of the results of the experimental work,obtained using the accelerometer and the magnetometer of the mobile device, and the pressure sensor connected to the BITalino device placed on the chair. It also presents the characteristics of the population involved in the experiences, limitations and conditioning factors for the data calculation [48].

The fifth contribution of this dissertation consists of the presentation and the statistical analysis of the results of the experimental work, obtained using the Electrocardiography and Electroencephalography sensors to detect its variations during the test, presenting the characteristics of the population involved in the experiences, limitations and conditions of the data calculations [49].

Finally, the last contribution consists of the use of artificial intelligence algorithms for the automatic identification of age, diseases, and groups of diseases of the population during the performance of the Timed-Up and Go test [50].

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2. State-of-the-Art

This chapter presents the state-of-the-art of this Master's Dissertation, and it is composed by two articles, each presented in its section. These two articles are focused in a review of the Timed-Up and Go Test with technological equipment.

2.1. Is The Timed-Up and Go Test Feasible in Mobile Devices? A Systematic Review

The following article is the first part of the chapter 2.

Is The Timed-Up and Go Test Feasible in Mobile Devices? A Systematic Review

Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, Gonçalo Marques, Nuno M. Garcia, Nuno Pombo, Susanna Spinsante and Eftim Zdravevski

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Review

Is The Timed-Up and Go Test Feasible in Mobile Devices? A Systematic Review

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Abstract: The number of older adults is increasing worldwide, and it is expected that by 2050 over 2 billion individuals will be more than 60 years old. Older adults are exposed to numerous pathological problems such as Parkinson's disease, amyotrophic lateral sclerosis, post-stroke, and orthopedic disturbances. Several physiotherapy methods that involve measurement of movements, such as the Timed-Up and Go test, can be done to support efficient and effective evaluation of pathological symptoms and promotion of health and well-being. In this systematic review, the authors aim to determine how the inertial sensors embedded in mobile devices are employed for the measurement of the different parameters involved in the Timed-Up and Go test. The main contribution of this paper consists of the identification of the different studies that utilize the sensors available in mobile devices for the measurement of the results of the Timed-Up and Go test. The results show that mobile devices embedded motion sensors can be used for these types of studies and the most commonly used sensors are the magnetometer, accelerometer, and gyroscope available in off-the-shelf smartphones. The features analyzed in this paper are categorized as quantitative, quantitative + statistic, dynamic balance, gait properties, state transitions, and raw statistics. These features utilize the accelerometer and gyroscope sensors and facilitate recognition of daily activities, accidents such as falling, some diseases, as well as the measurement of the subject's performance during the test execution.

Keywords: older adults; inertial sensors; physical exercises; physiotherapy; systematic review; timed-up and go test measurement

1. Introduction

People with disabilities or older adults are two essential groups that can benefit from technology advancements. Currently, around 9% of the world's population is aged 65 and above, and approximately 10% of the world's population lives with a disability [1,2]. Consequently, in countries with life expectancy over 70 years old, people spend on average about eight years, or 11.5 per cent of their life span, living with disabilities [1]. The increasing number of older adults is another cause for the growing number of people with impairments [1].

The number of older adults is increasing worldwide, and it is expected that by 2050, two billion individuals will be older than 60 years [3,4]. In parallel, the proliferation of information and communications technology brings numerous applications to the development and implementation of numerous methods for enhanced personalized healthcare systems [5,6]. Furthermore, the research interest in mobile computing technologies that focus on novel healthcare applications to promote public health and well-being is also increasing [7–9].

The use of mobile devices by older people was evaluated with the use of questionnaires and interviews [10]. In general, most older people only uses mobile phones for emergency situations, i.e., voice calls, and only a few of them use these devices for SMS and video calls [11,12]. Furthermore, mobile devices incorporate high processing power, numerous sensors, and connectivity methods for short-range and long-range communications [13]. Mobile devices are used in the implementation of numerous methods for clinical evaluation and personalized healthcare [14–17]. Several mobile sensors such as accelerometers, magnetometers, and gyroscopes that are incorporated in the majority of today's smartphones can be used to support numerous clinical evaluation procedures such as activity recognition and fall detection [18–22]. The continuous technological enhancements on mobile sensing promote novel applications for enhanced living environments and well-being; however, the collaboration between information and communications technology and medical researchers is mandatory for the efficient applicability of these methods [23].

The development of these solutions is related to the progress of the Ambient Assisted Living (AAL) domain, fueled using different types of sensors, that should not be intrusive and at the same time correctly positioned to acquire reliable data [24]. There are plenty of studies that demonstrate the applicability of mobile device sensors for recognition of different physical and physiological parameters, including the recognition of Activities of Daily Living (ADL) [25,26], environments [27], or even for reduction of false alarms in intensive care units [28]. Likewise, mobile devices have been used for the measurement of the results of the Heel-Rise test [29], proving that the implementation of physiotherapy tests is feasible with the mobile device sensors.

The Timed-Up and Go (TUG) test is a quick and straightforward clinical method for assessment of lower extremity function, mobility, and fall risk [30]. During it, the person is performing the following actions: getting up from the chair, walking for 3 meters, turning around, walking another 3 meters in a reverse direction, and sitting down on the chair. The typical duration of this test is a maximum of 12 seconds.

This method has been used to evaluate numerous individuals with pathological problems such as Parkinson's disease, amyotrophic lateral sclerosis, post-stroke, and orthopedic disturbances [30,31]. Therefore, clinicians would benefit from the implementation of mobile sensors to support efficient and effective methods for pathological symptom evaluation to promote agile interventions for enhanced public health [32].

A specific example of how a sensor-enhanced version of the TUG test outperformed the stopwatch version at classifying fall risk is provided in [33], demonstrating that measuring accelerometry during the TUG test improved the classification of fallers to 87% (compared with 63% using duration alone). Other publications, such as [34], have reported considerably higher scores of the stopwatch TUG test. An additional justification for performing TUG tests on a smartphone instead of the simple smartwatch version is the automated data collection and measurement [35] that can facilitate additional long-term analysis that could discover trends in the results of a single patient. This could lead to early detection of health issues and concerns before they come to a serious level [36].

Nowadays, artificial intelligence is taking a major role in the medical field. Numerous emerging applications of artificial intelligence methods have been designed and developed for enhanced patient treatment [37]. The TUG test has also been used to measure the functional performance of patients during their recovery process using unsupervised machine learning methods by several studies [38–41]. The calculation of features can be integrated with the feature engineering and selection process in a systematic way for supervised learning problems, such as in [25,42].

The main contribution of this paper is synthesizing the existing body of knowledge and identifying common threads and gaps that would open new research directions about the application of TUG tests on mobile devices. Furthermore, this literature review provides a comparison between the duration of the TUG test and the features used.

This work presents a systematic review of studies published between 2010 and 2018, focused on the application of the available sensors in off-the-shelf mobile devices to AAL and physical therapy, and specifically for the automation of the measurements performed during the TUG test [43]. The Timed-Up and Go test is especially important for the treatment and diagnosis of Parkinson disease and fall risk prediction [44–46]. For this purpose, this test analyzes the movement and recognizes different patterns related to various diseases, facilitating identifying future risky situations. The Timed-Up and Go test is executed in five distinct phases: (1) the individual sits in a chair (see Figure 1a); (2) the individual walks 3 meters (see Figure 1b); (3) the individual reverses the gait (see Figure 1c); (4) the individual walks back (see Figure 1d); and, finally, (5) the individual sits back in the chair (see Figure 1e). Throughout this test, the movements and speed can be measured using the embedded inertial sensors in smartphones. As a result, it is possible to identify patterns that highlight issues related to falls of older adults. It is noteworthy that several results presented, in general, calculations of the individuals' angles of movements or the speed and acceleration throughout the test. Several statistical methods and people of different ages were used for differentiating and defining patterns, which allowed for validation of the studies [47–52].

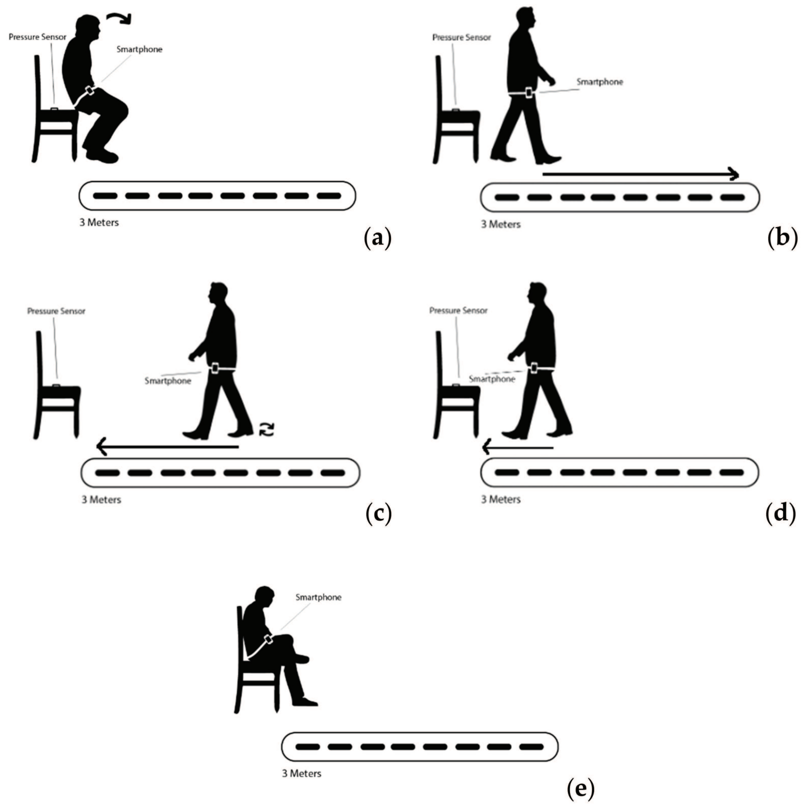

Figure 1. Timed-Up and Go test execution phases. (**a**) the individual sits in a chair; (**b**) the individual walks 3 meters; (**c**) the individual reverses the gait; (**d**) the individual walks back; (**e**) the individual sits back in the chair.

There are different types of TUG tests, including the standard TUG test, the Extended TUG test, the Smart Insole TUG test, and the Instrumented TUG test. The TUG test consists of a set of five phases, as represented in Figure 1 [43]. The Extended TUG test also includes a set of five stages [53], including standing up from a chair, walking for a ten meters distance, turning around, walking back to the chair and sitting down. The Smart Insole TUG (SITUG) test implements the TUG test with a Smart Insole device to provide real-time and fine-grained results in a more multifaceted analysis for the fall risk evaluation [54]. The Instrumented TUG (ITUG) test uses sensors to perform quantitative data extraction during the TUG test [55].

This remainder of the paper is organized as follows. Section 2 defines the applied methodology, explaining the research questions, the inclusion criteria, and the search strategy. Section 3 presents the results of this systematic review, which are subsequently discussed in Section 4. Finally, Section 5 concludes the paper.

2. Materials and Methods

2.1. Research Questions

The primary research questions of this review were as follows: (RQ1) In what ways are low-cost inertial measurement unit (IMU) sensors used to enhance TUG? (RQ2) Which methods for analysis of the TUG test results can be implemented on mobile devices? (RQ3) In what ways can IMU sensors improve the automation of TUG for assessing fall risk?

2.2. Inclusion Criteria

The inclusion criteria of studies and assessing methods for measurement of the results of the TUG test were: (1) Studies that measure the parameters of the TUG test using sensors; (2) Studies that present different approaches relative to the TUG test; (3) Studies that utilize at least motion or magnetic sensors; (4) Studies that focus on the use of sensors embedded in mobile devices; (5) Studies that were published between 2010 and 2018; (6) Studies which correctly define the participants population; (7) Studies written in English.

2.3. Search Strategy

The team searched for studies meeting the inclusion criteria in the following electronic databases: IEEE Xplore, ACM Digital Library, BMC, and PubMed. The research terms used to write this systematic review were: "Time-Up and Go test", "sensors", and "mobile devices". Every study was independently evaluated by eight reviewers, and its suitability was determined with the agreement of all parties. The studies were examined to identify the different approaches relative to the measurement of the results of TUG test, using the onboard sensors available in an off-the-shelf mobile device.

2.4. Extraction of Study Characteristics

The following data were extracted from the studies and presented in Table 1: year of publication, population, purpose, devices used, sensors available, raw data available, source code available, implementation, and studied diseases. We contacted the corresponding author of each study by email and asked for the source code and raw data. The implementation column groups the articles in two categories: "Calculation of the features" and "Implementation of machine learning methods". The "Calculation of the features" includes analytical features, such as angular velocity, which is not directly measured by the sensors, but rather derived from the original sensory measurements while considering the time factor. In general, the applicable statistical metrics on such sensors for this domain as well as their mathematical definition are provided in [42]. The second group of articles goes beyond and utilizes such features as inputs to machine learning models which are automatically trained and tuned.

Table 1. Study analysis.

Paper	Year of Publication	Population	Purpose of the Study	Devices	Sensors	Raw Data Available	Source Code Available	Implementation	Studied Diseases
Yang et al. [56]	2018	10 patients aged between 19 and 44 years old	Prevention of fall risks in the elderly subjects with the TUG test	Smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Healthy people
Bao et al. [57]	2018	12 subjects aged between 65 and 85 years old	Shows the efficacy of the balance training to help the elderly, using the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Healthy people
Yang et al. [54]	2018	6 subjects with unknown age	Appreciate the feasibility of the TUG test and using a complex system	Smartphone	Accelerometer Gyroscope	yes	yes	Implementation of machine learning methods	Healthy people
Silva et al. [58]	2018	18 older adults aged between 68 and 78 years old	Methodology to prevent and identify fall risks, using sensors and based on the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Rheumatic diseases; chronic pain; hypertension; dizziness; polypharmacy
Hellmers et al. [59]	2018	157 subjects aged between 70 and 85 years old	Automated analyses using inertial measurement units and the TUG test	Smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Parkinson disease
Chigateri et al. [60]	2018	23 older adults aged 75 years old or over	Measure the fall risk using sensors and the TUG test	Mobiles devices	Accelerometer	no	no	Calculation of the features	Healthy people
Mellone et al. [61]	2018	49 subjects aged between 43 and 75 years old	Validate a method for measuring the TUG test	Smartphone	Accelerometer	no	no	Calculation of the features	Parkinson disease
Madhushri et al. [62]	2017	10 geriatric patients aged between 78 and 86 years old	Mobility assessment with the TUG test	Smartphone	Gyroscope Accelerometer	no	no	Calculation of the features	Mobility problems
Beyea et al. [63]	2017	12 individuals aged between 21 and 64 years old	A mobile device using sensors and the TUG test separated in the different phases of the test	Mobiles devices	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Healthy people
Coni et al. [64]	2017	239 subjects aged between 65 and 93 years old	Study the decline associated with the evolution of age using the TUG test and sensors	Smartphone	Accelerometer Gyroscope	no	no	Implementation of machine learning methods	Healthy people
Salarian et al. [65]	2017	28 subjects aged between 52 and 68 years old	Instrumented the TUG test using sensors in people with Parkinson's disease	Mobiles devices	Accelerometer	no	no	Calculation of the features	Parkinson disease

Table 1. *Cont.*

Paper	Year of Publication	Population	Purpose of the Study	Devices	Sensors	Raw Data Available	Source Code Available	Implementation	Studied Diseases
Suppa et al. [66]	2017	28 patients aged between 63 and 77 years old	Inspect and associate the gait in people with Parkinson's disease using the TUG test and the sensors	Mobiles devices	Microsoft Kinect Accelerometer Gyroscope	no	no	Implementation of machine learning methods	Parkinson disease
Madhushri et al. [67]	2016	2 patients with unknown age	Application for mobility assessment helping the elderly to use the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Mobility problems
Cippitelli et al. [68]	2016	20 subjects aged between 22 and 39 years old	Quantify the possibility of the falls using data captured with sensors and tested with TUG test	Computer mobile devices	Microsoft Kinect Accelerometer	yes	no	Implementation of machine learning methods	Healthy people
Williams et al. [69]	2015	5 subjects aged between 21 and 36 years old	The system that helps the subjects in stroke rehabilitation using the TUG test	Smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Healthy people
Cuesta-Vargas et al. [70]	2015	30 subjects over 65 years old	Evaluation of the people and their mobility difficulty using sensors embedded in the smartphone and using the TUG test.	Smartphone	Accelerometer	no	no	Calculation of the features	Frailty syndrome
Milosevic et al. [71]	2015	7 subjects with unknown age	Application to automate instrumented the TUG test using sensors	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Parkinson disease
Dzhagaryan et al. [72]	2015	4 subjects with unknown age	Wearable system for older adults using the TUG test	Small wearable computing; smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Healthy people
Greene et al. [73]	2014	124 older adults aged between 69 and 83 years old	The mobile platform using inertial and pressure sensors to check the mobility of older adults, using the TUG test	Mobiles devices	Accelerometer Gyroscope	no	no	Implementation of machine learning methods	Frailty syndrome
Galán-Mercant et al. [74]	2014	30 subjects aged over 65 years old	Quantify and describe the acceleration, angular velocity and the motions of the body using a smartphone and the TUG test	Smartphone	Accelerometer	no	no	Implementation of machine learning methods	Frailty syndrome
Galán-Mercant et al. [75]	2014	18 subjects aged over 70 years old	Quantify and define the magnitude of inertial sensors using a smartphone test assessment, based on the TUG test	Smartphone	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Frailty syndrome

Table 1. *Cont.*

Paper	Year of Publication	Population	Purpose of the Study	Devices	Sensors	Raw Data Available	Source Code Available	Implementation	Studied Diseases
Greene et al. [76]	2014	21 patients aged between 18 and 60 years old	Examine the consistency of the quantifiable measures derivate of sensors and utilizing the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Calculation of the features	Multiple sclerosis
Galán-Mercant et al. [53]	2014	5 subjects aged over 65 years old	Analyze and quantify the reliability criterion-related with the utilization of sensors and using the extended TUG test	Smartphone	Accelerometer	yes	no	Implementation of machine learning methods	Healthy people
Tacconi et al. [77]	2014	3 subjects with unknown age	System to analyze the human falls using the TUG test	Smartphone	Accelerometer	no	no	Calculation of the features	Healthy people
Mellone et al. [22]	2014	200 subjects aged over 65 years old	Smartphone solutions to prevent and detect the human falls using the TUG test	Smartphone	Accelerometer Gyroscope	no	no	Implementation of machine learning methods	Healthy people
Bernhard et al. [78]	2012	384 subjects aged between 40 and 89 years old	Analyses the effectiveness of mobile devices using sensors and the TUG test	Smartwatch	Accelerometer Gyroscope Magnetometer	no	no	Calculation of the features	Parkinson's disease; stroke; epilepsy; pain syndromes; multiple sclerosis; tumors; polyneuropathy; vertigo; dementia; meningitis; encephalitis
Palmerini et al. [79]	2011	49 subjects aged between 28 and 87 years old	Motion analysis systems incorporated in a smartphone, to study the possibility of falls for people with Parkinson's disease using the TUG test and inertial sensors	Smartphone	Accelerometer	no	no	Calculation of the features	Healthy people
King et al. [80]	2010	28 subjects with unknown age	Predict the risks of falls, using a BSN attached with inertial sensors using the TUG test	Mobiles devices	Accelerometer Gyroscope	no	no	Calculation of the features	Healthy people

3. Results

As illustrated in Figure 2, our review identified 265 papers that included twenty-four duplicates, which were removed. The remaining 241 works were evaluated in terms of title, abstract, and keywords, resulting in the exclusion of 95 citations. The main criterion for the exclusion of papers was because 95 articles were not related to the applicability of mobile sensors available in an off-the-shelf mobile device. We performed the full-text evaluation of the remaining 146 papers, excluding 118 articles that did not match the defined inclusion criteria. The remaining 28 papers were included in the qualitative synthesis and quantitative synthesis. In summary, our review examined 28 documents.

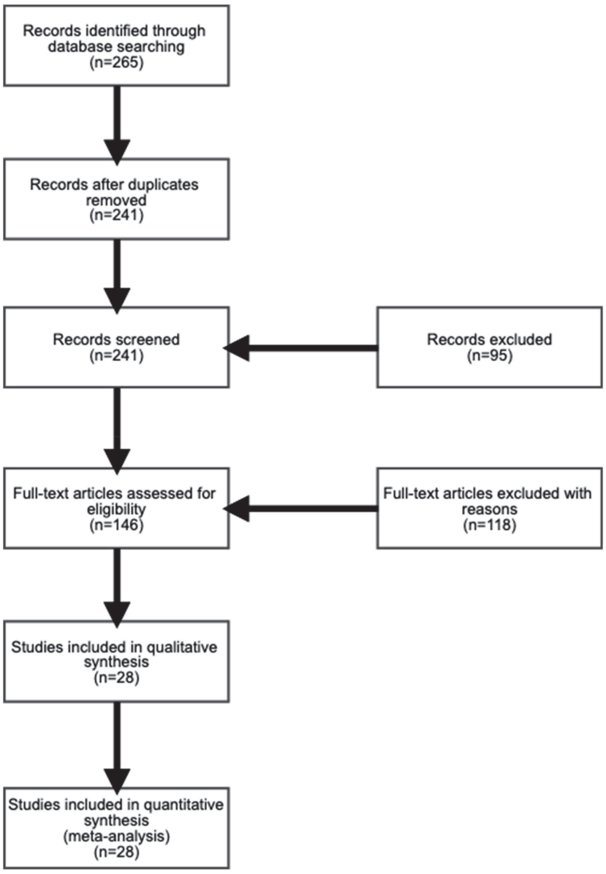

Figure 2. Flow diagram of identification and inclusion of papers.

We refer the interested readers to the original cited works to find relevant information about the details of the TUG test measurements analyzed in this review. As shown in Table 1, all studies were performed with mobile devices. The studies analyzed were published between 2010 and 2018 with one study in 2010 (4%), one study in 2011 (4%), one study in 2012 (4%), seven studies in 2014 (25%), four studies in 2015 (14%), two studies in 2016 (7%), six studies in 2017 (21%), and seven studies in 2018 (25%). The analyzed studies indicate that 20 studies used smartphones (71%) and eight used other types of mobile devices (29%). Therefore, related to the sensors used in the analyzed studies, the studies indicate the sensors used were the accelerometer in 27 studies (97%), the gyroscope in 19 studies (68%), and the magnetometer in seven studies (25%). Moreover, only eight studies (29%) present the accuracy of the results obtained with the different experiments related to the TUG test. Finally, the analysis of the diseases by the different studies was researched, where 14 studies (50%)

performed the TUG test with healthy people, 5 studies (18%) analyzed people with Parkinson's disease, four studies (14%) analyzed people with frailty syndrome, and, the remaining 5 studies (18%) analyzed people with other diseases.

The following sections present the results categorized by the different diseases listed in Table 1.

3.1. Healthy People

The authors of [56] implemented a method to assess the subject's balance, proposing four environment adapters designed to evaluate the ability to adapt to walking in complex environments associated to a compatible system that provides, in real-time, characteristics spatially related to walking. Thus, the authors proposed a four environment-adapting TUG test to asses one's aptitude to adjust gait in multifaceted environments and a compatible system called Smart Insole TUG (SITUG) [56]. These report an average precision of 92% and 23% in the segmentation of the 5 phases of the TUG test [56]. The features used in the study are the duration, the threshold of the forefoot, the limit of the rearfoot, the full contact time, the foot-ground contact time, the non-foot-ground contact time, the initial contact time, the gait cycle time, the gait cycle count, the gait cycle pace, the stride length and the sole average pressures [56]. The results show that SITUG reports an accuracy of over 92% in the recognition of the different phases of the test [56].

In [57], the authors evaluated the efficacy of long-term balance training with and without inertial sensors. Participants attended the sessions at home with one 45-minute session per week, using smartphone balance trainers that provided written, graphic, and video guidance, and monitored trunk sway [57]. The sensors, including gyroscopes and accelerometers, were used to measure angular changes [57]. They also estimated the duration of the TUG test as well as the gait speed, fast gait speed, sit-to-stand duration, and others [57].

The authors of [54] proposed a SITUG test to obtain the motor performance information in complex environments, to identify the probability of falls. The authors calculated the time variance, reporting an average accuracy of 94.1% in the extraction of subcomponents within a stride, and 93.13% in deriving the stride length based on the distance travelled [54]. Thus, the five phases of the test were recognized with an accuracy of around 90%, using pressure features, spatial features, temporal features, and spatial-temporal features [54].

In [60], the authors proposed the assessment of automatic real-time feedback provided by a shoe-mounted inertial-sensor-based gait therapy system is feasible in individuals with gait impairments after incomplete spinal cord injury. A way to identify parameters associated with gait was proposed, implementing several tests, including the TUG test with an accelerometer sensor [60]. The median overall agreement between the processed accelerometer data and the annotated video was an approximate match of 92.8% and 95.1% for walking episodes in scripted and unscripted activities, respectively [60]. In addition, based on the duration of each activity, the results reported an accuracy of 92.2% for recognition of the non-walking event and 88.7% for the recognition of walking activity

Beyea et al. [63] developed a protocol to acquire the Inertial Measurement Unit (IMU) data and measure the results of two versions of the TUG test, such as a test with 3 meters walking and another with 5 meters walking to compare the performance based on the different durations. The authors recognized the different phases of the test and calculate the average of the acceleration and the time of the TUG test [63]. Finally, the authors calculated the total time of the test and walking times, reporting an accuracy of 87% in the recognition of the different phases of the test [63].

In [64], the authors proposed research on the functional decline associated with ageing and its differences through a set of sensor-based measures by using the Instrumented TUG test, recognizing the different activities. The authors also examined the decline related to age-related and gender-related variances through a set of sensor-based measures [64].

Based on the TUG test, Cippitelli et al. proposed fall detection algorithms using the Inertial Measurement Units (IMUs) and an RGB depth sensor (Microsoft Kinect) [68]. The authors identified the sit-to-stand, walk, turn, walk, and turn-to-sit phases [68]. The authors also evaluated the maximum inclination of the torso angle and the time required to perform the movement [68]. They implemented three algorithms, where the first algorithm reports an accuracy of 79%, the second one presents an accuracy of 90%, and the latest algorithm shows an accuracy of 99% [68]. The orientation angle must be around 90° during a not very extensive period to check the fall [68].

In [69], a system to rehabilitate patients who have suffered a stroke was proposed, implementing the Smart Insole TUG test at the individuals' own homes. They measured the angles, stride length, total distance traveled, average velocity, and execution time of the TUG test, and identified the sitting and standing activities [69]. This system, featuring a simple configuration and a relatively low cost, provides feedback to the user, showing that it is possibly even better than current physiotherapy methods [69]. The system also checks the health status of knees [69]. The results show that the difference between the app's timer and the mobile devices represents a difference a Root Mean Square Error (RMSE) of 0.907 [69].

In [72], the authors introduced a wearable system titled Smart Button designed to assist the mobility of older adults and assess people with Parkinson's and the elderly with regards to the movement, balance, strength limits, and risks of falling, while calculating the highest and lowest accelerations as well as the angular velocity. The parameters extracted from the TUG test are total duration of the TUG test, active TUG test, and lift-up phase of the sit-to-stand transition, the length of the lean forward period, and the duration of the lift-up phase of the sit-to-stand, maximum change, and maximum angular velocity during the trunk angle in the lean-forward, maximum angular velocity during the lift-up, duration of the stand-to-sit transition, duration of the prepare-to-sit in the stand-to-sit, duration of the sit-down phase in the stand-to-sit, and number of steps during the walking phase [72].

The authors of [53] proposed the evaluation of the reliability and concurrent criterion validity of the acceleration using a smartphone application, inertial sensors, and the Extended TUG test. They implemented the Bland–Altman method with the data acquired from the accelerometer available in the mobile devices to obtain the different results [53]. Thus, they identified the sit-to-stand, gait-go, turn, gait-come, and stand-to-sit activities with the features available in a previous study protocol and the angles of the movement [53].

Based on a mobile platform, the authors of [77] presented a system for the study of falls and mobility, using the data captured by an inertial sensor and the Extended TUG test for validation. They calculated several features, including total, gait, sit-to-stand, and stand-to-sit durations, Root Mean Square (RMS) of sit-to-stand and stand-to-sit, maximum acceleration, mean cadence, cadence standard deviation, and cadence coefficient of variation [77]. The algorithm chosen was the single-threshold algorithm, and several simulations were made for the detection of falls, including forward fall, lateral fall, backward fall, fall sliding against a wall final position vertical, fall slipping against a wall, and falling out the bed actions [77].

A study presented by [22] is based on the techniques for the implementation of FARSEEING using smartphones to detect falls and prevent falls. The inertial sensors are used in the smartphone to calculate the probabilities of fall. For this application, they created a mobile application to perform the tests and use the TUG test as a study centre [22]. Based on the orientation of the device, the authors proposed a wearable system to identify the reasons for the falls using inertial sensors and the TUG test [22]. The results show the total duration and the maximum acceleration during the trial [22].

The authors proposed a method that uses accelerometer available in the smartphone as a measurement system for people with Parkinson's disease using the TUG test [79]. They extracted different features, including the duration, RMS, preparatory RMS and jerk of the sit-to-stand transition, the mean and standard deviation of step duration, phase coordination index, mean phase of gait phase, and maximum value of acceleration during the stand-to-sit period, recognizing the different stages [79].

The authors of [80] used a body sensor network (BSN) to detect the equilibrium to forecast falling. They extracted the mean, variance, number of peaks, and time as features to quantify 3100 amplitudes related to left–right movements, 2600 magnitudes related to up–down movements, and

2450 amplitudes related to forward–back actions [80]. For this purpose, they calculated the Tinetti score and the maximum and minimum amplitudes with the TUG test [80].

3.2. Parkinson Disease

The authors of [59] authors proposed the use of wearables for the assessment of gait and balance features in a clinical setting with an inertial measurement unit to use in people with Parkinson's disease for the evaluation of the possibility of falls using the TUG test. They extracted the auto-correlation, mean, pitch, standard deviation, RMS, energy, signal magnitude area (SMA), signal vector magnitude (SVM), spectral entropy, and correlation as features for the recognition of the different activities during the TUG test [59]. They reported that the use of self-learning methods presents a maximum acceleration of 12 m/s^2 and an angular velocity of 3 m/s [59].

The study presented in [61] evaluated the efficiency of the smartphone and its inertial embedded sensors in the implementation of the TUG test, and validation of the measurement of activity in frail elder people using inertial sensors. They extracted the total duration, jerk and range of sit-to-stand transition of the trial, the mean, and standard deviation of the step time, among others [61]. The reported results showed a balance when the smartphone was used and the McRoberts Hybrid device, which demonstrates that embedded sensors and smartphones are a viable alternative to more expensive equipment [61].

The study in [65] proposed the use of the instrumented TUG test with inertial sensors to improve the TUG test evaluation in several situations, employing automatic detection and separation of subcomponents, detailing the analysis of each of them and achieving a higher sensitivity than the TUG test. The Instrumented TUG test was different concerning the angular velocity duration of the turn, and the turning duration, and the time to perform turn-to-sit [65].

Suppa et al. [66] used the TUG test to examine and compare the gait in patients with Parkinson's disease for the recognition of freezing of gait based on the duration of the TUG test, and implemented treatment for the disease, reporting accuracy of 98% in recognition of the different phases of the test.

In [71], the authors presented a mobile application named sTUG that completely automated the ITUG test, measuring the total duration of the TUG test, sit-to-stand transition, and lean forward and lift phases in the sit-to-stand. Also, other features were measured, including the maximum change of the trunk angle, and maximum angular velocity during the lean forward and lift-up phases, the duration of the stand-to-sit transition, and the prepare-to-sit and sit-down periods in the stand-to-sit transition [71].

3.3. Frailty Syndrome

The authors of [70] implemented a method for the measurement of the Extended TUG test with a smartphone, identifying kinematic variables obtained with the inertial sensors, measuring the averages of time and the acceleration during the TUG test. The highest accuracy in discrimination between frail and non-frail elderly was reported as a value around 72.8% in recognition of the different phases of the test [70].

Based on the use of inertial sensors available on a mobile platform and other pressure sensors, the authors of [73] discussed the falls of older adults and the causes of serious injuries using the TUG test. The authors recognized different activities with 52 features quantifying the temporal, spatial, turning, and rotational characteristics [73]. The reported precision of the TUG test was a minimum accuracy of 78.11% in recognition of the different activities, and a minimum accuracy of 72.31% in recognition of the different phases of the test [73].

Galán-Mercant et al. [74] developed a method to measure and describe the angular velocity and acceleration variations and the trunk deviation with the Extended TUG test, to analyze the changes between healthy and frail individuals, and to identify the different activities. The significant difference between the groups in the sub-phases of sit-to-stand and stand-to-sit was in the vertical axis and vector, where the minimum acceleration in the stand-to-sit phase was –2.69 m/s^2 in the frail elderly and –5.93 m/s^2 in the non-frail elderly [74].

The authors of [75] used the smartphone application using inertial sensors as a measurement device to measure. They described the magnitude of acceleration values with frail and non-frail individuals. The features extracted are the maximum and minimum values of the acceleration of each axis [75]. Finally, they reported that the most significant differences were verified in the use of the accelerometer with eyes closed and the feet parallel with a maximum acceleration on the lateral axis of ($p < 0.01$), minimum acceleration peak on the lateral axis ($p < 0.01$), and peak acceleration of the resulting vector ($p < 0.01$) [75].

3.4. Other Diseases

The authors of [58] extracted several features for the recognition of the different phases of the Instrumented TUG test, including RMS, standard deviation, median deviation, interquartile range (IQR), skewness, kurtosis, number of times the magnitude signal crosses the mean value, maximum and second maximum frequencies of the fast Fourier transform (FFT), maximum and second maximum amplitudes of the FFT, minimum, maximum, average of the peak height, energy, and entropy.

The authors of [62] developed a customized three-segment form to quantify body forces and evaluate the optimization of each sit-to-stand transition. The evaluation of the model was performed by testing the action and optimal transition time for 10 older adults, comparing their best performance with the best performance of the model to use the results to evaluate possible improvements in the mobility of individuals [62]. They calculated the real angles and the averages of the sit-to-stand transition time and the actions of 10 geriatric patients 80 years old [62]. Using mobile phone inertial sensors and a smartphone mounted on the chest, the total power and action of each stand up during the test verified the force action derives between 170 joules at 0.2 seconds and 250 joules at 2 seconds [62].

Madhushri et al. proposed a smartphone application for assessing flexibility in the aged population using inertial sensors [67]. They also presented a set of applications to evaluate the implementation of the Smart Insole TUG test with older adults, extracting several parameters from the inertial sensors [67]. The parameters extracted include the duration of the TUG test, the sit-to-stand transition, the lean forward phase, the stand-to-sit shift, the prepare-to-sit period, the sit-down phase, and the lift up phase, the total time of walk, the maximum change of trunk angle during the lean forward phase, the maximum angular velocity during the lean forward and the lift up phases, the total number of steps during walking, and before turn [67]. The average error for the implementation of the Smart Insole TUG test is around 2% [67].

The authors of [76] implemented the TUG test with inertial sensors for the assessment of the disability status in people with sclerosis disease, measuring the time of the different phases, the angular velocity peaks as well as other spatiotemporal and statistic features. Moreover, this study also examines the reliability of the TUG test [76]. The authors tried to verify the existence of some diseases like Parkinson's and its evaluation [76].

The authors of [78] explored options using wearables, which can provide more objective information for the evaluation of hospitalized neurological patients, with an assessment procedure that gets acceptance in the communities. Based on the TUG test, the authors validated the use of inertial sensors embedded in a smartphone, extracting the angles of the movement [78].

4. Discussion

As it emerges from this systematic review, we can verify the importance that mobile devices have for studies related to the health of elderly subjects. Among the most evaluated variables or features, it has been identified that the studies in this area go a long way towards temporal measures, such as duration, and for angular measures, such as the angular velocity. Finally, it should be noticed that the sensors embedded in mobile devices are an inexpensive way to carry out studies of this importance, i.e., the accelerometer, gyroscope, and magnetometer. Also, they reported a high level of efficiency and they are used in numerous research studies. However, several artificial intelligence methods such as machine learning can be used for enhanced TUG test data analysis.

The TUG test consists of the execution of different activities. After the analysis, it was verified that the most used sensor in the literature is the accelerometer. Also, the most used features in the research are the duration of the test, the average of the angles obtained with the raw data, the edges of the movement, the number of steps, the maximum change of the trunk angle, the threshold, and the full contact time. In the normal TUG test, the most widely used features for the measurement of the different parameters of the test are the duration, the mean and standard deviation, and the RMS of the raw data extracted from the embedded sensors the mobile device (Table 2). Secondly, in the Extended TUG test, the most used features for the measurement of the different parameters of the test are the duration, the acceleration, and the number of steps extracted from the data acquired by the sensors available in the mobile devices (Table 2). Finally, in the Smart Insole TUG test, the most used features for the measurement of the different parameters of the test are the duration and the stride length extracted from the data acquired by the sensors available in the mobile devices (Table 2). The most used features are highlighted in Table 2.

Table 2. Features relative to the different types of Timed-Up and Go tests.

Features	Interpretation	Number of Studies		
		TUG	Extended TUG	Smart Insole TUG
Duration	Quantitative	6	3	6
Number of steps			2	1
Stride length				2
Step time		1		
Orientation		1		
Position		1		
Step length		1		
Cadence		1		
Turning duration		1		
Time to perform turn-to-sit		1		
Reaction time			1	
Contact times (i.e., initial, forefoot, rearfoot, full, foot-ground, and non-foot-ground)				1
Distance				1
Threshold				1
Standard deviation of the step time	Quantitative + Statistic	1		
Cadence standard deviation			1	
Cadence coefficient of variation			1	
Mean cadence			1	
Averages of time			1	
Mean stride length			1	
Medio-lateral and medio-lateral interstride autocorrelations		1		
Maximum change of the trunk angle		1		
Acceleration	Dynamic balance		2	
Maximum angular velocity		2	1	1
Average speed			1	
Averages of the sit-to-stand transition		1		
Real velocity		1		
Average velocity				1
Angular velocity of arm-swing		1		
Gait speed	Gait properties	2		
Gait duration			1	
Gait cycle time				1
Gait cycle count				1
Gait cycle pace				1

Table 2. *Cont.*

Features	Interpretation	Number of Studies		
		TUG	Extended TUG	Smart Insole TUG
Real angles of the sit-to-stand transition	State transitions	2		
Range of sit-to-stand transition		1		
Jerk		1		
Mean of raw data	Raw statistic	3		
Standard deviation		3		
Root mean square (RMS)		3	1	
Signal energy		2		
Signal magnitude area (SMA)		2		
Signal vector magnitude (SVM)		2		
Spectral entropy		2		
Variance		1		
Number of peaks		1		
Median deviation		1		
Interquartile range (IQR)		1		
Skewness		1		
Kurtosis		1		
Number of times the magnitude signal crosses the mean value		1		
Maximum frequency of the FFT		1		
Maximum amplitude of the FFT		1		
Minimum average		1		
Maximum average		1		
Average of the peak height		1		
Energy		1		
Entropy		1		
Angles				1
Maximum change of trunk angle				1

The Interpretation column in Table 2 shows the category of the feature: quantitative, which explains some aspects of the TUG test or another physical characteristic; quantitative + statistic, which denotes a derived quantitative feature with some statistical operation; dynamic balance, which mainly describes the dynamic balance of the person; gait properties, which can help in describing the gait specifics and can help in identifying some gait abnormalities; state transitions, which contribute to better discerning different states and transitions from between them; and raw statistic, which denotes features calculated with a statistical function directly on the raw sensory data.

The main strengths of the methods rely in the capability to demonstrate that it is possible to establish that people with different diseases can perform this test, obtaining different results. The data acquired from the sensors allows accurate calculation of different results of this test, where the use of low-cost sensors may help in the obtention of results by the healthcare professionals belonging to the physiotherapy domain.

There is no information available regarding the confidentiality and protection of data acquired during the experiments. We performed a rigorous evaluation of each study to verify the existence of a validation of the study protocol by a human subject research ethics committee, but the information was not conclusive. Thus, we contacted the authors and research group to obtain more clarifications about the data protection of each study, but we have not yet received the responses.

The results of this review demonstrate that the data acquired from the sensors available in off-the-shelf mobile devices may be used to identify patterns in the acquired data depending on different diseases. Consequently, it is possible to reveal patterns of the diseases related to the test by grouping persons with different diseases. On the one hand, the results show that the data acquired from the sensors available in off-the-shelf mobile devices facilitate the detection of different diseases such as Parkinson's disease, amyotrophic lateral sclerosis, post-stroke, and orthopedic disturbances.

On the other hand, the TUG test can be performed reliably by the patients without having to visit physiotherapists. Likewise, physiotherapists can monitor the progress of a disease by having an integrated and reliable log of patient's TUG test results for an extended period of time.

However, there is no correlation between the most used features for each type of analysis and each study. Also, any research uses the most used features at the same time, and the studies have different purposes, including the measurement of various parameters and recognition of the different activities.

The measurement of the general TUG test has some limitations, as presented in [45]. By instrumenting the TUG test with sensors and by extracting multiple features in addition to the duration, we aim to overcome these issues:

- Falling risk in healthy older populations may not affect the measurement of the duration;
- The user may perform the different phases with other involuntary movements or trajectories;
- The effects of the medication therapy and movement deficiencies may not be detected;
- The high reliability and discrimination of the health may not be evaluated in only 3 meters;
- The measurement of the results of the test depends on the personal and environmental conditions;
- The conditions of the chair may also introduce the possibility of different results.

Generally, all studies use multiple features in a single recognition model. Despite the fact that some features are redundant to some extent, which could be intuitively understood solely by their mathematical definition, the recognition systems use them. The motivation is that while only a few of them are most important for recognition of a task, for an alternative task, some others would be useful. For example, for simply scoring the TUG test, the duration is usually enough. However, for fall detection, other features become important. Even more features are required for detection of more complex Activities of Daily Living.

Even though most studies do not provide specific ranges of the values of certain features to help in understanding the classifications, for any "black box" classification model, there are methods, such as local interpretable model-agnostic explanations (LIME) [81] or SHAP (shapley additive explanations) [82], which efficiently provide insights in the classification process.

Several studies have been performed, but a framework for the use of the TUG test for the recognition of different diseases and automation of the calculation of the various parameters of the test with low-cost sensors is still not available. Finally, the creation of a standard for the evaluations of the physical conditions with this type of test is essential.

As a result of the review of the related works, we believe that a standard for conducting the TUG test on mobile devices can be defined. Most importantly, multiple approaches show that simple statistical features based on the raw time-domain data is sufficiently accurate. Therefore, such computation is feasible on mobile devices with limited computing and battery capacity. For this test, more complex approaches, such as ones relying on deep learning models, are not recommended. Another recommendation is that mobile devices performing this test need to be integrated with the electronic health records of patients and to be available for their doctor, when required and after the approval of the patient. Of course, this raises many other technical challenges related to privacy and security. However, this can be proved instrumental in allowing the doctor to identify complex emerging patterns, such as progress of a disease, and to be able to act upon it proactively, instead of reactively.

5. Conclusions

This systematic review analyzes, verifies, and identifies the use of inertial sensors available in the mobile devices to detect movements and reactions during the TUG test. The use of sensors together with these tests allows drawing essential conclusions about how to prevent falls in the elderly or those with a disabling disease, and how measures can be created that can help avoid these events. In general, several approaches to the topic of typical use of technology (mobile devices and sensors) and health areas are reported in the literature. Motion sensors with more demanding architecture can capture more data more accurately and with greater efficiency. Thus, combined with a constant evolution of mobile technology and mobile devices, it is possible to achieve a continually growing number of events previously mentioned due to the increased life expectancy. Finally, the test that was the central target of this analysis is an adequate test, with excellent use for its ease of implementation and it does not require large equipment or technological devices to be carried out. Along with mobile devices using open source technologies, the TUG is very accessible to all.

Twenty-eight studies were examined, and the main findings are summarized as follows:

- (RQ1) Most of the low-cost IMU sensors used in the TUG tests are the gyroscope, magnetometer, and accelerometer. These sensors are widely used in the physiotherapy domain and can be used to detect all the five phases of the TUG test, which can be identified by sensors available onboard off-the-shelf mobile devices. Moreover, mobile sensors can be a low-cost approach for the TUG test and consecutively to clinical diagnostics of several diseases. The data collected by mobile sensors can be analyzed to create patterns for the evaluation of different diseases.
- (RQ2) The methods and features most used to measure the results are related to the time of the TUG test, the angular velocity and the angular analysis of the body movements, and the number of steps performed.
- (RQ3) One of the main purposes of the TUG test is to help in the recognition of the probability of the risk of falls, where eight studies present the relation between it and the TUG test in elderly people.

In conclusion, the literature review identified numerous studies reporting applicability of the TUG test for multiple evaluations in the medical domain, namely for detection of different diseases such as Parkinson's disease, amyotrophic lateral sclerosis, post-stroke, and orthopedic disturbances. The reviewed studies claim that the embedded sensors on mobile devices increase the reliability of the test. Therefore, the ubiquitous mobile devices present a low-cost, efficient, and reliable tool for performing the TUG test.

In the future, personal digital life coaches can be designed to evaluate different parameters of the subjects' physical conditions for medical and recreational use. Such systems, depending on the application scenario, would rely on multiple machine learning algorithms to cope with computational and battery limitations, while aiming to provide exceptional accuracy.

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2.2. Identification of Diseases Based on the Use of Inertial Sensors: A Systematic Review

The following article is the second part of the chapter 2.

Identification of Diseases Based on the Use of Inertial Sensors: A Systematic Review

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Review

Identification of Diseases Based on the Use of Inertial Sensors: A Systematic Review

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Abstract: Inertial sensors are commonly embedded in several devices, including smartphones, and other specific devices. This type of sensors may be used for different purposes, including the recognition of different diseases. Several studies are focused on the use of accelerometer signals for the automatic recognition of different diseases, and it may empower the different treatments with the use of less invasive and painful techniques for patients. This paper aims to provide a systematic review of the studies available in the literature for the automatic recognition of different diseases by exploiting accelerometer sensors. The most reliably detectable disease using accelerometer sensors, available in 54% of the analyzed studies, is the Parkinson's disease. The machine learning methods implemented for the automatic recognition of Parkinson's disease reported an accuracy of 94%. The recognition of other diseases is investigated in a few other papers, and it appears to be the target of further analysis in the future.

Keywords: accelerometer; wearable electronic devices; diseases; monitoring; ambulatory; automatic identification; parkinson's disease

1. Introduction

Ageing is presently a critical challenge worldwide, which is particularly relevant in developed countries [1–3]. In total, 9% of the population is over 64 years old worldwide, and 10% will have disabilities [4,5]. Ageing will lead to relevant impacts on the economy and society, associated with costs in healthcare [6,7]. The scenario in Portugal is not different, as it is in the top five countries with older adults worldwide [8–10]. It is relevant to mention that Portugal was the country with the highest birth rate in Europe, 45 years ago [11,12]. However, Portugal is now at the top of the list with fewer births in Europe [13,14]. Accordingly, the dependency of older adults associated with a low birth rate will lead to even more social impacts and demands for the design and development of novel and efficient strategies to promote the health and well-being of citizens [15].

The Ambient Assisted Living (AAL) concept includes multiple research domains to design improved software tools and healthcare systems for enhanced living environments [16,17]. However, different challenges still exist in the design of AAL technologies associated not only with the reception of these tools by older adults but also related to privacy and security [18–20].

Healthcare systems combine different software and hardware systems to provide multiple services not only to promote the quality of life of patients but also to support healthcare staff [21,22]. Personal healthcare devices are used for several telemedicine tasks using portable systems to monitor the patient's physical signs [23,24]. These devices can observe distinct parameters, such as blood pressure, oxygen, and medication intake, but they are also used to supervise patients' behavior and detect falls [25,26].

Presently, mobile devices such as smartphones and tablets include high power processing properties and incorporate multiple non-invasive sensors that are used to design efficient and cost-effective healthcare solutions [27,28]. Mobile healthcare applications also support patient participation in their disease prevention and management and consequently contribute to relevant cost savings [29–31]. Moreover, mobile devices incorporate multiple short-range and long-range communication protocols such as GPRS (General Packet Radio Service), 3G, HSDPA (High-Speed Downlink Packet Access), 4G, 5G, Bluetooth, NFC (Near-field communication) and Wi-Fi. These communication technologies facilitate patient monitoring in hospitals, medical facilities, and in patient's homes [32–34]. Furthermore, wearable devices currently include the same sensors as smartphones and are consequently used to supervise cardio-metabolic [35], and electroencephalogram (EEG) signals [36], in a non-invasive manner [37–39]. To summarize, mobile devices must be seen today as an essential and crucial part of personalized healthcare procedures not only for monitoring activities but also for clinical evaluation and disease detection [40–42].

The accelerometer, magnetometer, and gyroscope sensors incorporated in mobile devices or other commercial board modules are compatible with different interfaces, such as I2C, UART (Universal Asynchronous Receiver-Transmitter) and PWM (Pulse Wave Modulation). They can be applied in the context of enhanced healthcare, such as activity recognition and automatic disease detection [43–45]. The accelerometer is used in numerous clinical evaluation tasks, both incorporated in wearable-based systems or using mobile devices [46,47]. Countless people suffer from multiple diseases, causing a variety of consequences on their physical activity and mobility, such as postural instability and gait disturbances, which can lead to independence reduction and loss of movement [48–51]. Consequently, the use of automated processes for disease evaluation plays a significant role in enhanced public health.

The cross-domain knowledge sharing combining computer science and healthcare can lead to the design of effective systems for enhanced personalized healthcare assessment, which can also be supported by artificial intelligence methods to create novel techniques for automated disease recognition. On the other hand, this multidisciplinary approach can provide novel solutions to face the worldwide challenges related to ageing and the quality of personalized healthcare [52–55].

This paper presents a review of state-of-the-art accelerometry-based systems and methods for the automatic identification of various diseases. We aim to provide a comprehensive understanding of the different healthcare conditions that can be recognized, monitored, and evaluated using accelerometry devices and artificial intelligence techniques.

The main contribution of this paper is the synthesis of the existing body of knowledge, presenting the collective outcomes and limitations that must be analyzed to point out new research directions. Furthermore, we compare different methods and extract the most significant insights from the analyzed literature. As a result, this paper aims to provide a practical background not only to academics or computer science engineers but also to healthcare professionals.

The structure of this document is the following: Section 2 presented the strategy used to conduct this systematic review and describe the research questions, and the criteria for the literature section. The results are shown in Section 3, and they are later discussed in Section 4. Finally, the conclusions are presented in Section 5.

2. Materials and Methods

Systematic reviews use formal explicit methods, of what exactly was the question to be answered, how evidence was searched for and assessed, and how it was synthesized to reach the conclusion. The "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement" [56] is one of the most widely used methodologies for achieving this, therefore we have applied it in this work. For this type of studies, it is essential that they are statistical valid with enough individuals in a studied population. In continuation, the diseases that can be detected with these sensors is important to define a method for the recognition, where the recognition differs by each disease. The authors have conducted a systematic review of papers published after 2008 to provide a comprehensive, but not limited analysis considering 12 years of studies regarding the automatic detection of studies using inertial sensors. Finally, the use of artificial intelligence methods is important for the automatic recognition and measurement, and this review intends to discover which as the methods used in the literature.

2.1. Research Questions

The primary research questions of this review were as follows: (RQ1) How many people are involved in the different studies related to the use of the inertial sensors? (RQ2) Which diseases can be detected with inertial sensors? (RQ3) Which artificial intelligence methods are used for the identification or recognition of different diseases?

2.2. Inclusion Criteria

The inclusion criteria of studies and assessing methods for the automatic identification of various diseases using the accelerometer sensor were: (1) Studies that perform recognition of diseases related to the movement; (2) Studies that use at least an accelerometer sensor; (3) Studies that were published between 2008 and 2020; (4) Studies that defined the number of participants; (5) Studies written in English.

2.3. Search Strategy

The team searched for studies meeting the inclusion criteria in the following electronic databases: IEEE Xplore, ACM Digital Library, ScienceDirect, MEDLINE, and PubMed. The research terms used to identify relevant articles for this systematic review are: "diseases", "accelerometer", and "automatic identification" or "automatic recognition". Initially, we employed a tool that leverages Natural Language Processing algorithms [57] to remove duplicate articles and narrow down the potentially relevant articles. Afterwards, five reviewers independently evaluated every study, and its suitability was determined with the agreement of all parties. The studies were examined to identify the different diseases that can be identified with the use of data acquired from the accelerometer sensor.

2.4. Extraction of Study Characteristics

The following information was extracted from various articles analyzed and presented in Tables 1 and 2: year of publication, population, purpose, sensors used, diseases detected, accuracy, and outcomes of the different studies. The corresponding authors of the various papers were contacted to obtain more information about the different studies. We evaluated the identified studies based on the qualities related to the research questions, considering the number of participants (an explicit number should be stated in the study), the sensory devices (also need to be explicitly mentioned), which diseases are being automatically identified, and which artificial intelligence algorithms were applied for automatic recognition of the disease. Based on these parameters, the studies' quality was assessed. In general, the most detected disease is Parkinson's disease and other diseases related to the various walking patterns.

Table 1. Study analysis.

Paper	Year of Publication	Population	Purpose of the Study	Sensors	Diseases Detected	Accuracy
Viteckova et al. [58]	2020	26 healthy adults and 25 subjects with Parkinson's disease	Compare and quantify the results of repeated performance over time and the performance of healthy and sick people with Parkinson's disease	Accelerometer and Gyroscope	Parkinson	N/A
Sharif Bidabadi et al. [59]	2019	30 healthy subjects and 56 patients with Lumbar radiculopathy and related ankle dorsiflexion weakness with observable foot drop	Use of inertial measurement unit using machine learning methods to distinguish gait disturbances	Accelerometer, Gyroscope, and Magnetometer	Lumbar radiculopathy and related to ankle dorsiflexion weakness with observable foot drop	93.18%
Stamate et al. [60]	2018	22 individuals with Parkinson's disease	Develop an application to create an extensive data set of motor characteristics of individuals with Parkinson's disease	Accelerometer	Parkinson	95%
Joshi et al. [61]	2017	15 patients with Parkinson's disease and 16 healthy control subjects	Method to analyze gait variables for Parkinson's patients	Accelerometer	Parkinson	90.32%
Ribeiro et al. [62]	2016	Five volunteers with recent episodes of Epilepsy	Development of a technique using machine learning, to automatically recognize people with epilepsy	Accelerometer	Epilepsy	99%
Djuric-Jovicic et al. [63]	2014	12 patients with idiopathic Parkinson's disease	Method for the detection of walking disorders for people with Parkinson	Accelerometer and Gyroscope	Parkinson	98.55%
Gruenerbl et al. [64]	2014	12 bipolar disorder patients	Demonstrate how smartphones can be used to aid the diagnosis of people with psychiatric disorders	Accelerometer and GPS receiver	Bipolar	80%
Pendharkar et al. [65]	2014	Ten children with idiopathic toe walkers and ten children with a normal gait	Automated classification of heel accelerometer data	Accelerometer	Idiopathic Toe Walkers	97.9%
Kugler et al. [66]	2013	Five healthy adults and five subjects with Parkinson's disease	Make an automatic classification between healthy individuals and people with Parkinson's disease using walking electromyography	Accelerometer and electromyography (EMG) sensor	Parkinson	N/A
Barth et al. [67]	2012	17 healthy adults and 18 subjects with Parkinson's disease	System to analyze the motor function of the hand and to walk to differentiate healthy people and people with Parkinson's disease	Accelerometer and Gyroscope	Parkinson	97%
Alaqtash et al. [68]	2011	Ten healthy adults and four relapsing-remitting multiple sclerosis patients	Wearable system for the acquisition of gait parameters	Accelerometer	Multiple Sclerosis	N/A
Phan et al. [69]	2008	30 subjects with recent symptoms of arrhythmia or sleep apnea	Accelerometer system to compare efficiency in detecting heart disease, compared to traditionally used tools	Accelerometer and electrocardiography (ECG) sensor	Arrhythmia or sleep apnea	N/A
Garcia Ruiz et al. [70]	2008	28 patients with idiopathic Parkinson's disease	Analysis of the utility and correlation of Active Appearance Model (AAM) with timed tests and Unified Parkinson's Disease Rating Scale (UPDRS) scores with people with Parkinson's disease	Accelerometer	Parkinson	N/A

Table 2. Study outcomes.

Paper	Outcomes
Viteckova et al. [58]	The authors intended to use the instrumented Timed-Up and Go test, repeatedly in young adults and people with Parkinson's disease to make comparisons and test the efficiency of the method. Various related features were calculated, with the test time and the other parameters related to walking and angular velocity. An Xbus Mater was used for data acquisition, which includes 5 accelerometers with a sampling rate of 100 Hz.
Sharif Bidabadi et al. [59]	The study aimed to investigate disorders related to falls in people with low back problems and used machine learning algorithms. Machine learning was implemented to use an accelerometer to acquire data. The results showed that the performance was better with the use of the three classifiers Random Forest, Support Vector Machine (SVM), and Naive Bayes. In contrast, when the wrapper feature technique was used, the highest accuracy was 93.18% with the Random Forest classifier. The accelerometer used is a three-axis accelerometer to measure the different directions of movement.
Stamate et al. [60]	A cloud application called Unified Parkinson's Disease Rating Scale (UPDRS) was presented as a tool for people with Parkinson's disease. The system features a workflow compatible with various formats of audio, video, and text media. It consists of an Android application for testing, a cloud system for saving data, and a data mining tool kit for medical intelligence that incorporates quantitative data and semi-structured and longitudinal analyzes, groupings, and classifications. The data was acquired by the accelerometer embedded in 9 different phone models with a sampling rate of 50 Hz.
Joshi et al. [61]	The authors implemented a wavelet analysis method combined with the SVM method for Parkinson's patients. Various parameters related to walking were calculated, namely stride interval, swing interval, and stance interval (from both legs). The results showed an accuracy of 90.32%. The data was acquired by a three-axis accelerometer with specificity of 93.75%.
Ribeiro et al. [62]	The study used machine learning methods for the automatic recognition of people with epilepsy. Five machine learning methods were used to determine the most efficient among Naive Bayes, k-Nearest Neighbors (kNN), C4.5, Support Vector Machine (SVM), and Decision Tree-based-method (PART). The results showed that kNN had the highest computational cost, and PART and C4.5 had the lowest. Furthermore, the sensor used by the system was a three-axis accelerometer.
Djuric-Jovicic et al. [63]	The authors presented a method to identify the problem of falls in people with Parkinson's disease. Several types of stride were considered, and some features (namely Shank Movement Displacement, stride duration, and shank transversal orientation) were calculated. The results showed the highest performance of the algorithm was achieved when using a type of FOG stride with 100% accuracy. The data was acquired by a three-axis accelerometer with a minimum specificity of 87.8%.
Gruenerbl et al. [64]	The authors intended to use smartphones to help diagnose people with mental disorders such as depression and bipolar disorder. Inertial sensors and Global Positioning System (GPS) traces were used in the developed system. The results showed an accuracy level of 80%. The accelerometer used has a fixed sampling rate of 5Hz.
Pendharkar et al. [65]	The authors presented a method called Idiopathic Toe-Walking (ITW) to detect walking problems in children. The sensor used in this system was the accelerometer, with the two signals of horizontal and vertical acceleration decomposed to avoid overlap. The results showed that Blind Source Separation (BSS) techniques combined with a K-means classifier could distinguish gait from foot to normal pace in children with ITW with an accuracy of 97.9%. The sensor used is a dual-axis accelerometer.
Kugler et al. [66]	The authors presented a method of automatic recognition of people with Parkinson's disease. An accelerometer and an electromyography sensor were used to recognize and validate the walking parameters. When cross-validation to leave a subject out was used, the sensitivity and specificity values were the highest at 0.90, the best-rated features were the kurtosis and the mean frequency, and the best features had a significant difference in kurtosis of (p = 0.013). The authors used a three-axis accelerometer with a specificity of 90%.
Barth et al. [67]	The study featured a combined hand and leg analysis system for recognizing people with Parkinson's disease. Pressure sensors were used in conjunction with the accelerometer to analyze the hand. Moreover, gyroscope and accelerometer sensors were used to analyze the foot. The results were crossed between healthy individuals and people with Parkinson's disease, showing that when the AdaBoost classifier was used, the efficiency of the system reached 97%. These authors used a three-axis accelerometer, reporting a specificity between 88% and 100%.
Alaqtash et al. [68]	The authors presented a wearable sensor system for the acquisition of parameters related to walking by using a fuzzy computational algorithm, with healthy individuals and a group of patients with multiple sclerosis. The results showed that this system could be beneficial for the identification of problems related to walking showing the differences between healthy people and people with multiple sclerosis. This experiment used a dual-belt instrumented treadmill, which includes several three-axis accelerometers.
Phan et al. [69]	A system using the accelerometer was presented to detect diseases of the respiratory system and the heart. The system was positioned on the chest by using a belt. The study compared the use of traditional sensors such as an electrocardiogram (ECG) with a system implemented using an accelerometer. The results showed that the system provided identical results when the heart rate graph with the QRS complex was presented. This experiment considered the use of dual-axis accelerometer with high sensitivity.
Garcia Ruiz et al. [70]	The authors presented a method called ActiTrac for people with Parkinson's disease. The technique had the right level of efficiency in observing the motor part of the subjects participating in the study. The results showed that the mean activity significantly correlated with the total and the motor UPDRS scores. The accelerometer embedded in the ActiTrac device is a three-axis accelerometer.

3. Results

As presented in Figure 1, our review identified 98 papers that included one duplicate, which was removed. The remaining 97 studies were evaluated in terms of title, abstract, and keywords, resulting in the exclusion of 50 citations. The main criteria for excluding the papers were because 50 articles were not related to automatic recognition/identification of diseases with the accelerometer sensor. The full-text evaluation of the remaining 47 papers was performed, excluding 34 items that did not match the defined inclusion criteria. The excluded articles were not focused on automatic recognition of diseases by using accelerometer sensors, or because the diseases cannot be identified only with the accelerometer. As the focus of this study consists of the recognition of diseases related to the accelerometer sensor, i.e., diseases related to the movement, these articles must be excluded. The remaining 13 studies were presented in the qualitative and quantitative synthesis. In summary, our review examined 13 research articles.

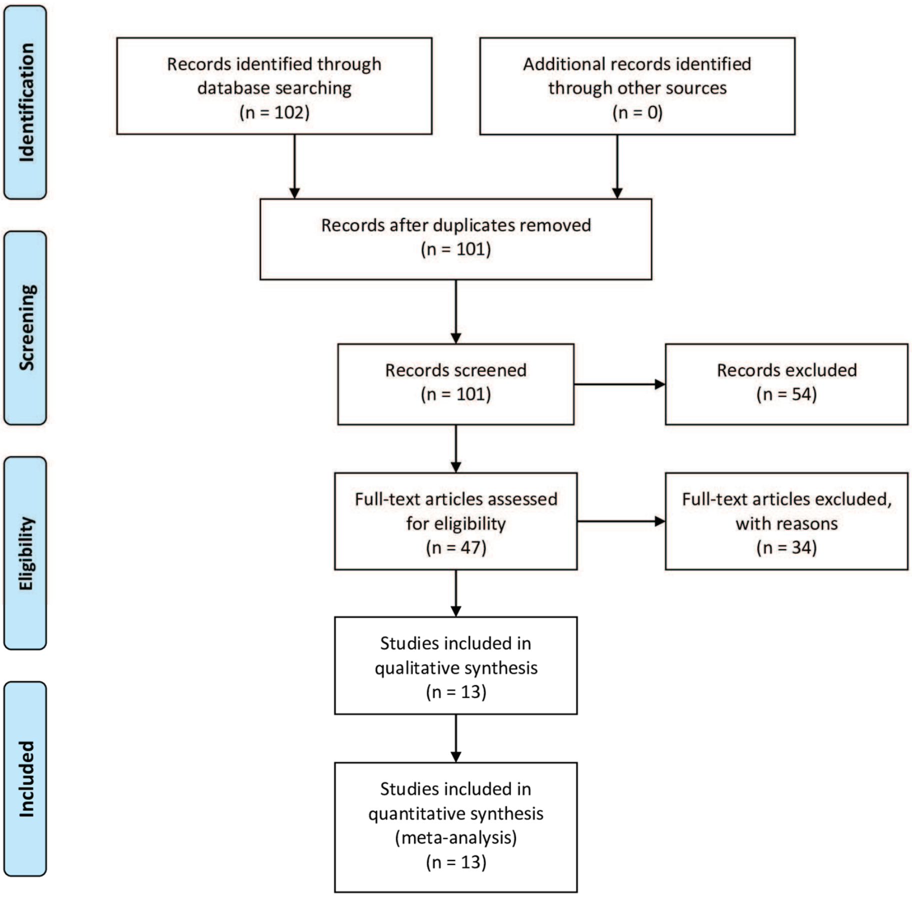

Figure 1. Flow diagram of identification and inclusion of papers.

After the analysis, the different research works are presented in Tables 1 and 2. For a more detailed analysis, the authors have also analyzed the year of each study and the location of the authors involved in the research. Also, the original studies are cited to obtain more detailed information. As shown in Tables 1 and 2, we analyzed the studies that provided an automatic recognition of the different diseases in studies that uses the accelerometer sensor. The studies analyzed were published between 2008 and

2020 with three studies in 2014 (23%), two studies (15%) in 2008 and 2018, and one study (7%) in 2011, 2012, 2013, 2016, 2017, 2019, and 2020, as presented in Figure 2.

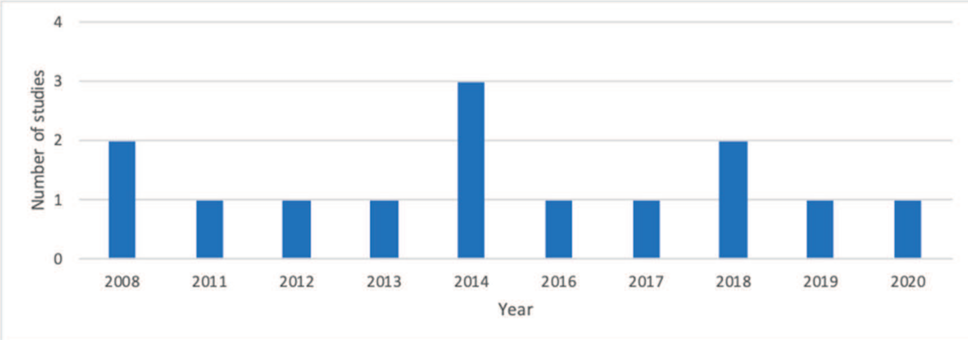

Figure 2. Distribution of the studies by different years of publication.

On average, the different studies considered the data acquired by a different number of people between 5 and 85 persons (27 ± 22 individuals), where the higher number of individuals increases the reliability of the study. The sensors used were studied, verifying that all searched items used the accelerometer sensors. Also, other studies combined the use of the gyroscope sensor (31%), the magnetometer sensor (8%), the GPS receiver (8%), the electromyography (EMG) sensor (8%), and the electrocardiography (ECG) sensor (8%). Finally, Parkinson's disease is the most detected disease with the accelerometer sensor, which was recognized in seven studies (54%). The remaining disorders are only identified in one study each: lumbar radiculopathy and related ankle dorsiflexion weakness with observable foot drop, epilepsy disease, bipolar disorder, idiopathic toe walkers, multiple sclerosis, arrhythmia, and sleep apnea. In general, the accuracies reported are reliable, reporting 94% accuracy (on average), but four studies (31%) did not present the accuracy of the recognition. Only two studies considered the use of dual-axis accelerometer (15%), where the remaining studies are using three-axis accelerometer (85%), because this type of sensors is the most common in the different devices.

The remaining results are categorized by the recognition of the different diseases, considering the detection of Parkinson's disease (Section 3.1), and other diseases (Section 3.2), because the other healthcare diseases recognized are residual.

3.1. Parkinson's Disease

The authors [58] presented the repeated use of instrumented Timed Up and Go test in adults and patients with Parkinson's under different conditions using accelerometer data. Multiple features have been calculated over the different experiences including total time, gait sub-component, peak, the velocity of arm swing, range of motion of arm swing, arm swing asymmetry, cadence, gait cycle time, double support, stride length, stride velocity, stride time variability, stride length variability, peak trunk rotation velocity, trunk rotation, range of motion, turn sub-component, average turning velocity, peak turning velocity, sit-to-stand sub-component, average, trunk velocity, peak trunk velocity, duration, and trunk inclination.

The authors [60] developed an application for evaluating people with Parkinson's disease. The system consists of three different elements, such as an Android application for capturing sensor data, iCloud-based technologies to store the data, and data mining techniques to obtain a better analysis of the captured data. Different parameters were analyzed during the experiments, including rest tremor, postural tremor, action tremor pronation-supination movements leg agility, finger tapping, and gait.

The authors [61] proposed a non-invasive method for classifying Parkinson's disease. Using wavelet analysis combined with the Support Vector Machine (SVM), this method has a high accuracy value. Several walking parameters were analyzed, namely stride interval, swing interval, and stance interval (from both legs). The study presents some limitations that were identified in the realization of the experiments, among which the group of people chosen did not have the same age range, the same range of weights and types, which may have influenced the results. On the other hand, as the gait rhythm was calculated based on a portable system, other parameters of walking analysis could be added, and different frequencies, which may have influenced the level of accuracy presented. Another limitation identified by the study's authors was the level of correlation between gait features, and the inertial unit of measurement (IMU) may be implemented in the future in Parkinson's or healthy individuals with the advantage of avoiding the lack of gait cycles. The Force Sensor data obtained the data in low sampling, but it did not achieve the high precision rate required in a study of this type.

The authors [63] presented an algorithm for the detection and classification of disorders during gait in people with Parkinson's disease. These types of disorders are classified as difficult to detect. The algorithm separates normal and abnormal gait using the statistical method of Pearson's correlation. The data processing features several types of stride, including normal, short minus, short plus, freezing of gait (FOG) with tremor, FOG minus, and FOG with complete block engine. In general, they were being identified in 100% of the experiences of individuals with Parkinson's disease, namely 95% in Normal FOG and a minimum of 78% in Short FOG. Different types of classifications are presented for the performance of the algorithm related to sensitivity, specificity, accuracy, and precision, with the stride of the FOG type reported the best score of 100% in all parameters. Some other features are extracted such as Shank Movement Displacement, Stride Duration, and Shank Transversal Orientation.

The authors [66] presented a method to assist in the monitoring and progression of patients with Parkinson's, using the accelerometer and electromyography as sensors for data extraction. The control group used to carry out the experiments consisted of elements with Parkinson's disease and healthy, to validate the results of the study, and prove the effectiveness in detecting the disease. The electrodes were positioned bilaterally on anterior tibialis and gastrocnemius medialis and lateralis, while accelerometers on both heels and were used to segment the steps. Features of the Statistical and frequency type were extracted and then used to train the SVM classifier and automatic recognition of the disease. The results show that the best features were kurtosis and mean frequency, with a marked difference in the case of kurtosis that sensitivity and specificity were higher up to 0.90 using leave-one-subject-out cross-validation.

The authors [67] presented a combined analysis method for people with Parkinson's disease. The accelerometer, gyroscope, and pressure sensors were positioned at the patient's hand to acquire parameters related to gait. Several features of the signal sequence type were used, including mean, variance, regression line gradient, the standard deviation of minima, maxima minima difference, autocorrelation maximum, integral, and root mean square. Also, features related to frequency analysis were used, including dominant frequency, energy ratio, energy in the frequency band, and regression line of widowed energy in the frequency band. Moreover, the features related to step features were extracted, including the falling gradient of the stance phase. The results show an accuracy level of 97% in the combined analysis. On the other hand, it shows an accuracy of 89% in isolation and 91% in the gait analysis.

The authors [70] presented a system called ActiTrac for patients with Parkinson's to validate the classification of ambulatory activity monitor. Also, devices with accelerometers were used to record the strength of the muscles and the accelerations in position changes. The results obtained show reliability when correlated with Unified Parkinson's Disease Rating Scale (UPDRS) rigidity and bradykinesia subscores. Still, it does not show reliable results with the presence of tremor subscores. The Perdue Pegboard test, finger dexterity, and walking test are correlated with the duration of illness, but it is associated not with the clinical stage.

3.2. Other Diseases

The authors [59] presented a method to classify foot drop gait characteristics using machine learning algorithms in individuals with problems with lumbar radiculopathy. Different machine learning methods were used in this study. The ones that presented the best results in terms of accuracy were Random Forest, SVM, and Naive Bayes classifiers with 88.45%, 86.87%, and 86.08%, respectively, were applying the wrapper feature selection technique, it presents the best accuracy equals to 93.18%. Three inertial units of measurement (IMU) sensors were used for the acquisition of gait data. After that, the signal is transmitted via wireless. The sensors were positioned to the segments of the foot, stem, and thigh of the affected limb for patients (leg with falling foot) and the right leg for non-patients.

The authors [62] presented a method of machine learning for people with epileptic problems. A Wearable device was used to carry out the study considering F-Score and Accuracy metrics. The system used an Arduino board, Bluetooth communication, and an accelerometer connected to the Arduino. The machine learning techniques used were k-Nearest Neighbor (kNN), Decision Tree-based method (PART), and C4.5 Decision Tree. Still, kNN has a higher computational cost when compared to PART and C4.5 Decision Tree and PART a lower computational cost than C4.5 Decision Tree. The main objective of this work is to simplify and reduce the computational cost in recognition of day-to-day activities. Thus, a method was proposed to distinguish the different events of each day.

The authors [64] presented a study to analyze the use of smartphones in the diagnosis of people with mental disorders in people with bipolar disorder. The sensors used in this study were the accelerometer and the Global Positioning System (GPS) receiver, which obtained the following conclusions: patients with depression move less often, and more slowly, on the other hand, manic patients tend to run frequently and quickly. When we talk about travel patterns, people with this type of disorder travel less and with a less constant time pattern. The results show a recognition accuracy of 80% and a precision of 96% and a recall of 94% in recognition of state changes.

The authors [65] presented a method for analyzing gait in children. A technique called Blind Source Separation is used with Idiopathic Toe Walkers (ITW) children to identify gait parameters and detect walking problems in children. The sensor used in this system was the accelerometer having decomposed the two signals of horizontal and vertical acceleration so that there was no overlap. The results show that Blind Source Separation (BSS) techniques together with a K-means classifier can distinguish gait from foot to normal pace in children with ITW. The results show an average accuracy of 97.9%.

The authors [68] proposed an application with wearable sensors to analyze the walking parameters of healthy individuals with multiple sclerosis. An artificial intelligence algorithm called the fuzzy computational algorithm was applied. This algorithm was classified as being very promising for the health areas in helping to detect disorders related to the gait of individuals. The presented results did not report the classification accuracy, which is a limitation. On the other hand, the presented graphs allow us to perceive its efficiency as it is easily understood as the different results between healthy people and individuals with sclerosis. As future work, the authors present the possibility of developing methods that make it possible to make a quick analysis of disorders related to gait in individuals, efficient, low cost with more types of approaches. The accelerometer is the sensor used in this study, demonstrating once again the capabilities to analyze parameters related to acceleration force during gait.

The authors [69] presented a system for analyzing cardiorespiratory function using the accelerometer coupled to the chest using a belt. The authors state that this method may be useful to identify some diseases. The sensor detects the acquisition of data in different states (Normal, Apnea, and Deep Breathing) and vertical (sitting, standing) or horizontal (lying) postures, being the signal compared to frequency measurements performed by the electrocardiogram. The results show the efficiency of using the accelerometer in the detection of respiratory waves and heart rates. Presenting itself as an effective method in the discovery of some heart diseases such as arrhythmia or sleep apprehension.

4. Discussion

The data acquired from the accelerometer sensors allow the development of methods for the identification of different healthcare conditions, namely the diseases related to movement. Based on the various analyzed studies, we conclude that Parkinson's disease is the most identified disease with the accelerometer sensors. Some other disorders are marginally researched: lumbar radiculopathy and related ankle dorsiflexion weakness with observable foot drop, epilepsy disease, bipolar disorder, idiopathic toe walkers, multiple sclerosis, arrhythmia, and sleep apnea. The accelerometer acquires different data related to the acceleration of the movement that allows the identification of abnormalities during walking activity.

However, the accelerometer is available on different devices, including mobile devices and other specific types of equipment, such as the Bitalino device [71]. There are various problems related to the data acquisition that is mainly associated with the synchronism of the data transmission, the failures in the data acquisition, the sensitivity of the accelerometer used, positioning of the mobile device during the data acquisition, and other different hardware and software problems related to the devices used [72,73].

The accelerometer presents itself as a sensor with a multitude of uses in the acquisition of data related to the force and angular speed exercised by people during gait. It opens several opportunities for the automatic recognition of different diseases, and, consequently, the creation of disease patterns [74].

The acquisition of data from the accelerometer sensor combined with artificial intelligence methods allows for the recognition of different diseases, and the work of the healthcare professionals will be improved. Various machine learning techniques can be used, including k-Nearest Neighbor (kNN), Decision Tree-based method (PART), C4.5 Decision Tree, and kNN. However, these techniques need high processing capabilities, and, in most of the cases, the authors only compared the different features extracted from the accelerometer signal without the implementation of artificial intelligence techniques.

The different studies are dispersed by different countries with more incidence in Germany, the United Kingdom, the United States, Brazil, and Australia that concentrated more than five authors of the various studies (see Figure 3).

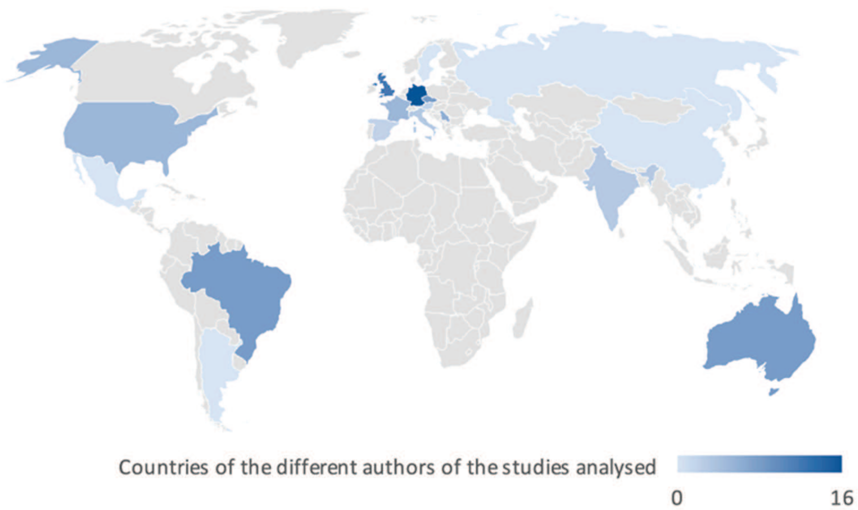

Figure 3. Geographical distribution of the different studies analyzed.

Numerous opportunities in this area have arisen, namely the detection of diseases, where the use of artificial intelligence methods facilitates its recognition. The use of automatic methods increases and speeds up the discovery of all parameters that may indicate the presence of specific disease and the individual's condition [55].

The increase in the percentage of older adults mainly in the western world and some standard protocols between research centers and those responsible for nursing homes has resulted in an increase in the number of studies to people where diseases, such as Parkinson's disease. Consequently, in the short term, this improves the speed of detecting this type of disorder and speeding up treatments.

As future work, we intend to identify different diseases based on the performance of the Timed-Up and Go test as the continuation of the work presented at [75,76]. The recognized disorders will be mainly related to the different abnormalities of movement, and other healthcare problems related to the lower limbs.

5. Conclusions

This systematic review paper presented a state-of-the-art analysis of the use of accelerometry-based systems that have emerged for the automatic recognition of multiple diseases. The authors aimed to provide a comprehensive understanding of the different healthcare conditions that can be evaluated using accelerometry devices. Moreover, we presented an analysis of the artificial intelligence techniques applied and their accuracy. The analyzed articles were published between 2008 and 2020. Most of the analyzed studies were conducted in 2014 (23%) and 2018 (15%). These studies were carried out by scholars from different countries with more incidence in Germany, the United Kingdom, the United States of America, Brazil, and Australia.

We analyzed 13 studies and obtained the following answers to the research questions considered:

- (RQ1) *How many people are involved in the different studies related to the use of the inertial sensors?* The number of volunteers involved in the studies analyzed ranged from 5 to 85 (27 ± 22 individuals), where the increasing number of individuals increase the reliability of the study.
- (RQ2) *Which diseases can be detected with inertial sensors?* Several diseases could be detected using accelerometer sensors such as Parkinson's, lumbar radiculopathy, and the related ankle dorsiflexion weakness with a noticeable foot drop, epilepsy, bipolar disorder, idiopathic toe walkers, multiple sclerosis, arrhythmia, and sleep apnea.
- (RQ3) *Which artificial intelligence methods are used for the identification or recognition of different diseases?* The artificial intelligence methods used for disease identification are Random Forest, SVM, Naive Bayes, kNN, C4.5, PART, and BSS, and K-means.

Furthermore, we concluded that the data from other sensors such as gyroscope, magnetometers, GPS receivers, EMG, and ECG were combined with the accelerometer data to identify multiple diseases. Parkinson's disease was the most studied disease using accelerometer sensors, representing 54% of the analyzed papers. Additionally, the average accuracy reported by the studies using artificial intelligence methods was 94% (on average).

In conclusion, multidisciplinary approaches creating a synergy between computer science and medical sciences can lead to the design of effective architectures that improve the processes related to the identification of different diseases. These architectures can incorporate artificial intelligence methods to create novel techniques for automated disease recognition and provide enhanced personalized health solutions to face the overall concern of healthcare in older adults and address the global ageing challenge.

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Conflicts of Interest: The authors declare no conflict of interest.

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3. Method for the analysis of the results of Timed-Up and Go Test

This chapter is related to the definition of the method for the measurement of the results of Timed-Up and Go Test with sensors, and it is composed by one article.

3.1. Smartphone-based automatic measurement of the results of the Timed-Up and Go test

The following article is the first part of the chapter 3.

Smartphone-based automatic measurement of the results of the Timed-Up and Go test

Vasco Ponciano, Ivan Miguel Pires, Fernando Reinaldo Ribeiro, Nuno M. Garcia, Nuno Pombo, Susanna Spinsante and Rute Crisóstomo

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ABSTRACT

The Timed-Up and Go test is a very used test in the physiotherapy area. For the measurement of the results of the test, we propose to use a smartphone with several embedded sensors, including accelerometer, magnetometer, gyroscope, a Bitalino device with the Electromyography (EMG) and Electrocardiography (ECG) sensors, and a second Bitalino device with a pressure sensor connected and positioned in the back of the chair. This architecture allows to capture several types of data from the sensors easily. In this paper, we present a structured method to implement the measurement of the different parameters involved in the Timed-up and Go test, for acquiring, processing and cleaning the collected measurements. This data will help in the classification of the test results initially, and later on to discover more complex patterns and related conditions, such as equilibrium changes, neurological pathologies, degenerative pathologies, lesions of lower limbs and chronic venous diseases.

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CCS CONCEPTS

• **Computing methodologies** → *Neural networks*; • **Applied computing** → *Computer-aided design*; *Health informatics*; *Bioinformatics*.

KEYWORDS

Data acquisition, Data processing, Data classification, Mobile application, Sensors.

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1 INTRODUCTION

The development of solutions related to health problems and care of elderly people carries several challenges for the adoption of technology [1, 17, 19].

Regarding to their size, portability and ease of use, ubiquitous systems such as smartphones become quite interesting because they facilitate access to data for use in the health area. On the other hand, the validation of these data becomes difficult due to the reluctance of the medical staff to adopt them, and the difficulty of obtaining clinical and scientific validation. Mobile devices can make a great contribution to this area, being smartphones equipped with Android operating system market leaders widely used in this type of studies [15], and because smartphones have several sensors, including accelerometer, magnetometer and gyroscope.

The development of these systems pertains to the domain of Ambient Assisted Living (AAL) systems [2, 5, 21], that can be useful for monitoring the elderly.

The purpose of this study consists in the definition of a technological architecture supporting a method for the automatic recognition of the different parameters collected during the Timed-Up and Go test, including the recognition of different diseases. The diseases related to the test are mainly equilibrium changes, neurological and degenerative pathologies, lesions of lower limbs and chronic venous disease.

The motivation of the study is to use these data and methods to create disease patterns, based on the Timed-Up and Go test results, to implement simple methods to aid in the identification of diseases.

This paper defines the sensors and the architecture enabling the measurement of the different parameters, and supporting approaches based on linear analysis and artificial intelligence, thus being able to use the sensors' data to create patterns that can identify possible associated diseases and establish standards with the data acquired for this research.

This paragraph finalizes the introduction, and the remaining sections are organized as follows: Section 2 presents the related work, including different types of data acquired, different methods used for data acquisition, frameworks and techniques used in these types of studies. The study design of the test, the position of the sensors on the body and the system architecture for data acquisition, processing and classification are presented in Section 3. Finally, Section 4 presents the discussion and conclusion of this study.

2 RELATED WORK

2.1 Data Acquisition

Sensors available in the mobile devices allow for the acquisition of different physical and physiological data, which may lead to measuring all the parameters encompassed in the Timed-Up and Go test [22, 25]. There are different frameworks that allow the acquisition of the sensors' data efficiently, taking in account the limitations of these devices, including: Acquisition Cost-Aware Query Adaptation (ACQUA) framework [10], Orchestrator framework [9], BBQ approach [12], Jigsaw framework [11], LittleRock prototype [16] and ErdOS framework [23]. Data acquisition should be performed with lightweight methods in order to reduce the constraints related to the battery and processing capabilities [14]. However, the data acquisition is performed efficiently without the use of frameworks with efficient techniques, and it is the most popular method in the literature [13].

2.2 Data Processing

Data processing includes two types of structured architectures, namely the Device Data Processing Architecture and the Server Data Processing Architecture [3].

The first one was designed with the purpose of acquiring the data of the sensors of the mobile devices and process them locally. This type of architecture is compatible with the use of mobile devices for the implementation of solutions that allow their execution in mobility, implementing lightweight methods in devices with low power processing, battery, storage and memory capabilities. On the other hand, Server Data Processing Architecture consists of sending the data to a remote server using high capabilities at the computation level and allowing for the treatment of larger amounts of data.

Data cleaning is one of the parts of the data processing that consists in the application of filters and statistical methods to adjust the values acquired from the sensors [7]. The data cleaning process is performed with temporal characteristics of the data acquired.

2.3 Feature Extraction and Data Classification

In this type of studies, the most used features are the duration, mean of raw data, standard derivation, signal magnitude area, energy, velocity, number of steps and others [8, 24].

After the extraction of features, its selection can be performed systematically and automated according different parameters as presented in [26].

In [6, 20], the risk of falls with the use of sensors embedded in the Smartphone and/or a wristband was performed. Several features were tested and classified such as Root Mean Square (RMS), median, standard deviation, skewness, kurtosis, maximum frequency of Fast Fourier Transform (FFT), maximum amplitude of FFT, FFT amplitude, average, average peak height, energy and entropy of motion and magnetic sensors, with methods for the calculation of features and their classification according to the results acquired in each test.

The authors of [24] aimed to make a test to calculate the probability of falls in complex environments, having the stride, the stride length, distance travelled and features of the spatial type of distance and target pressure to analyze to the level of their accuracy.

Finally, the authors refer to elderly individuals with different types of pathologies, being the measurement target of study the length of the step, duration of the posture, the balance or the angle of the foot on the soil [19].

3 METHODS AND EXPECTED RESULTS

3.1 Study design

The experimental setup will be applied to institutionalized people aged between 60- and 80-years with movement capacity. The development of this solution is related to the Ambient Assisted Living (AAL) systems [2, 5, 21], establishing a cooperation between several institutions, including the Polytechnic Institute of Castelo Branco, Portugal, Universidade da Beira Interior, Covilhã, Portugal, and Marche Polytechnic University, Ancona, Italy.

Timed-Up and Go test is composed by six phases, including: the individual seated; the individual rises from the chair; the individual walks for three meters; the individual turns around; the individual walks for three meters towards the chair and the individual returns to sit.

The test environment, presented in Figure 1, will be composed of a smartphone with an accelerometer, a magnetometer and a gyroscope. In addition, a pressure sensor will be positioned on the participants' waist, and an ECG and Electroencephalography (EEG) sensors are placed on the participants' body. All these sensors are connected to a Bitalino device.

The ECG is used to capture the variation of the heart rate and the EEG is used to capture the variation of the cerebral activity during the experiments. The sensors embedded in the smartphone: accelerometer, magnetometer and gyroscope are used to determine the body motion during the experiments, for example to verify if a participant is walking. The pressure sensors will be used to validate if the user is rising from the chair.

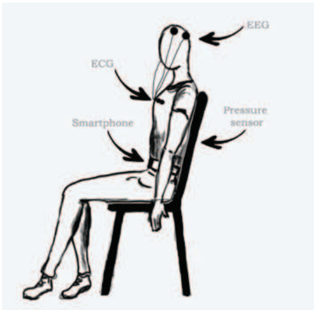

Figure 1: Positioning of the sensors during the test.

3.2 System Architecture

The system architecture, presented in Figure 2, is composed by several modules, comprehending the acquisition of the data from the sensors selected, the processing of the data acquired, that includes the stages to clean and extract the features from the data acquired, and the classification of the data. The classification is an important stage and it will help in the identification of different diseases and/or abnormalities present in the data acquired. The pressure sensor, ECG and EEG sensors will be used only to label the data in laboratory environment, so next in real time deployment it will not needed.

3.3 Methods for Data Acquisition

The acquisition of data in this system includes an accelerometer, a gyroscope, a magnetometer, a pressure sensor, an ECG sensor and an EEG sensor. The data acquired is saved on files that will be stored in a remote server with security and privacy requirements for further analysis.

3.4 Methods for Data Processing and Feature Extraction

After obtaining the data, they will be processed with the application of a low-pass filter. The low-pass filter helps in removing short-term fluctuations and provides a smoother form of signal. The data processing also comprehends the extraction of the different features, which include average, standard deviation, number of steps, time of the Timed-Up and Go test, time for each phase of the test, peaks and others. The most used features are mainly statistical features.

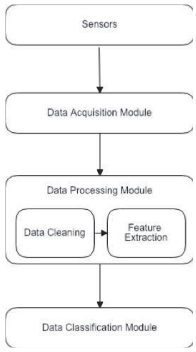

Figure 2: Different phases of the method implemented.

However, this study also makes use of Bitalino devices to obtain different types of data, including Electromyography (EMG), ECG and pressure sensors.

3.5 Methods for Data Classification

Based on the features extracted, a signal pattern will be established with machine learning methods, mainly Artificial Neural Networks (ANN) to validate the exercise and allow for the recognition of different types of diseases, including equilibrium changes, neurological pathologies, degenerative pathologies, lesions of lower limbs and chronic venous disease.

It comprehends the use of several sensors, implementing algorithms that incorporate techniques with linear analysis, ANN, Deep Neural Networks (DNN), Support Vector Machine (SVM) or other methods. The analysis of the ECG and the EEG features can identify some medical conditions to prevent some risk situations that can be detected with the test.

These methods should be implemented without the need for a network connection, implementing the different classification of patterns with local processing techniques implemented as lightweight methods onboard the smartphone.

The classification of the data will be based on the creation of patterns of individuals and associated diseases, or to verify if individuals with the same or similar limitations appear to have similar values and if they are within a standard deviation that will later allow for evidence for medical staff who may indicate that these individuals may have certain pathologies or not.

4 DISCUSSION AND CONCLUSIONS

This paper presents an approach for collecting and measuring sensors' data related to the Timed-Up and Go test by using smartphones, as well as the system architecture and different methods of collecting and processing the acquired data.

The data processing presents some problems when using mobile devices. If we use the device's data processing architecture, we will have problems at the level of the limit of storage, power processing and battery. On the other hand, if we use the Server Data Processing Architecture, we will have to consider that a good network connection will be necessary to transfer data with quality. The position of the sensors and the mobile device in relation to the body as well as the well-built environment are very important, causing some differences during the data acquisition. In addition, each mobile device can present a different level of accuracy in data acquisition.

Based on the method presented in [18], the proposed system is differentiated with the use of the sensors embedded in a mobile device and the EEG, the ECG and pressure sensors connected to a Bitalino device, because it provides low-cost sensors. The other study proposed the use of a high cost device named bioPlux that is more intrusive than the proposed devices, including the use of EMG sensors, placed in the femoral rectus, femoral biceps, Iliocostal lumbar and rectus abdominis, and an accelerometer sensor, placed on the head.

One of the most important phases for this study is the acquisition of data and the way it is processed and classified. From this point of view, it is possible to draw conclusions that could be very important for the study. The analyzed features of the collected data could identify patterns of diseases, and one can verify the usefulness of this type of studies in the clinical practice.

As future work, we aim to create a Personal Digital Life Coach [4] in the fields of physical therapy, sports and others, for people aiming at analyzing their physical conditions, using and including methods of artificial intelligence with the objective of recognition of different types of pathologies.

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4. Implementation of the Analysis of Timed-Up and Go Test with sensors

This chapter is related to the research and development of the method for the measurement of the results of Timed-Up and Go Test, and it is composed by three articles, each presented in its section.

4.1. Mobile Computing Technologies for Health and Mobility Assessment: Research Design and Results of the Timed Up and Go Test in Older Adults

The following article is the first part of the chapter 4.

Mobile Computing Technologies for Health and Mobility Assessment: Research Design and Results of the Timed Up and Go Test in Older Adults

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Article

Mobile Computing Technologies for Health and Mobility Assessment: Research Design and Results of the Timed Up and Go Test in Older Adults

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Abstract: Due to the increasing age of the European population, there is a growing interest in performing research that will aid in the timely and unobtrusive detection of emerging diseases. For such tasks, mobile devices have several sensors, facilitating the acquisition of diverse data. This study focuses on the analysis of the data collected from the mobile devices sensors and a pressure sensor connected to a Bitalino device for the measurement of the Timed-Up and Go test. The data acquisition was performed within different environments from multiple individuals with distinct types of diseases. Then this data was analyzed to estimate the various parameters of the Timed-Up and Go test. Firstly, the pressure sensor is used to extract the reaction and total test time. Secondly, the magnetometer sensors are used to identify the total test time and different parameters related to turning around. Finally, the accelerometer sensor is used to extract the reaction time, total test time, duration of turning around, going time, return time, and many other derived metrics. Our experiments showed that these parameters could be automatically and reliably detected with a mobile device. Moreover, we identified that the time to perform the Timed-Up and Go test increases with age and the presence of diseases related to locomotion.

Keywords: Timed-Up and Go test; sensors; mobile devices; accelerometer; magnetometer; pressure sensor; feature detection; diseases; older adults

1. Introduction

1.1. Background

The increasing age of the world population has promoted research in several areas and advances in different types of sensors, which have contributed to the evolution of healthcare assessment methodologies [1]. The increased life expectancy has led to growing interest and the need for solutions that can improve the quality of life of the elderly. In Europe, the aging rate was 125.8% in 2017, and 94.1% in 2001 [2–5].

Mobile computing technologies made it possible to aid individuals with different health statuses. They now include multiple sensors, which can be used for a verity of diverse functions [6]. The magnetometer and the accelerometer are essential because they facilitate the acquisition of physical and biological data from the user [7–9]. Moreover, these sensors can support the analysis of bodily functions like gait [10,11]. Furthermore, combining mobile computing technologies with external sensors can promote older people's quality of life [12]. However, in such studies, there are challenges related to choosing adequate tests, and interpretation and analysis of the collected data [13–17].

Embedded sensors may help to monitor the different functional tests with the detection of different types of movements [18–22]. The Timed-Up-and-Go test is a quick and straightforward clinical test for assessing lower extremity performance related to balance, mobility and fall risk in the elderly population and people with pathologies (i.e., Parkinson's disease, amyotrophic lateral sclerosis, in post-stroke patients, in patients with orthopedic pathologies, and cardiovascular incidents) [23–28]. Aging effects can be identified with the Timed-Up-and-Go test, and it could be supplemented with smart technology to be used in clinical practice [29]. The automation of the measurement of sensor data when performing the Timed-Up and Go test can be valuable, particularly in older adults [30,31]. Some approaches, such as [32], make it possible to perform the Timed-Up and Go test using low-cost devices in a real-time setting with reduced needs of processing capabilities to be used in commonly used devices.

1.2. Motivation

The Timed-Up and Go test can provide a practical analysis of the degree of prevalence and level of certain diseases [33]. With this test, clinicians can assess physical conditions by evaluating the way the individual walks, and the time it takes to perform the analysis. Therefore, this test allows the medical team to assess whether the individual has an accelerated degree of disease development or is in the initial state [34].

Furthermore, the Timed-Up and Go test can be used in individuals with neurological diseases [35]. This test allows for the evaluation of their reaction time. It is possible to assess whether they get up quickly or still stop for a long time. Moreover, it is possible to evaluate whether the individual walks in a straight line or cannot maintain the correct direction [36,37]. Therefore, this test can also provide a practical assessment of cognitive problems that do not allow him to follow the right path.

This test is widely used in assessing a patient's recovery process associated with diseases that have affected their mobility [38]. The data collected in this test support the evaluation of patient recovery to establish standards related to the reaction time, test time, angular derivation, and walking strength that an individual with different degrees of the disease might have [39].

This paper's motivation is to present a cost-effective method for the automatic measurement of the Timed-Up and Go test using sensors available on common smartphones. This document also states the calculation of numerous features that aim to create a reliable dataset for pattern recognition on specific health symptoms. Moreover, this study provides a comparative analysis of different subjects, which live in nursing homes separated by age, institution, and various diseases of people, finalizing with the comparison with the other results available in the literature to state the useful contribution of the proposed approach.

Finally, the major challenge with this is related to the definition of the best positioning of the sensors for the correct data acquisition. Thus, it affects the measurement of the different results of the Timed-Up and Go test, e.g., in case the experiments are performed under adverse conditions, the probability of having the incorrect measurement of the results is very high. Technological constraints may also affect the data acquisition and processing, such as low memory, power processing, connectivity, network, and battery constraints of the mobile devices [40,41]. Previously, we explored and presented the positioning of the sensors available in a mobile device or connected in a Bitalino device with the preliminary results in [42,43].

1.3. Prior Work

There are some studies available in the literature that involved the calculation of the different features related to the Timed-Up and Go test for further conclusions about the performance of the test. The inertial sensors, e.g., accelerometer, magnetometer, and gyroscope, available in a mobile device may be used to evaluate the benefits of the training based on the Timed-Up and Go test, calculating the velocity and the time of a sit-to-stand transition [44].

Fall risk assessment based on wearable inertial sensors was performed based on an instrumented Timed-Up and Go test in [45], relying on a variety of features, as summarized in Table A1. The types of gait and balance were evaluated with a similar set of features in [46]. The accelerometer sensor was used for the identification and measurement of the duration of each stage of the Timed-Up and Go test in individuals with spinal cord injury [47]. The different phases were also evaluated in [48] with an accelerometer sensor, measuring the mobility angles, and the average of the sit-to-stand transition time in frail elderly individuals with Parkinson's disease. In [49], the measurement of the Timed-Up and Go test results was performed with an accelerometer sensor for fall risk assessment. The different phases of the test for people with Parkinson's disease were analyzed in [50] and [51]. In [52], patients with Parkinson's disease were analyzed during a walking activity to measure the duration of the test. A smartphone application suite for assessing mobility is presented in [53]. Whether the individual was sitting during the Timed-Up and Go test is investigated in [32]. The authors of [54] perform analysis, mainly focusing on people with frailty syndrome. A wearable system for assessing mobility in older adults is presented in [55], relying on a variety of statistical features. Similarly, a wearable system for measuring the probability of human falls is introduced in [56], while [17] is concerned with identifying the reasons for falls. In [57], the authors show that the mobile device accelerometer can study and analyze the Romberg test's kinematic between frail and non-frail older adults.

In summary, Parkinson's disease was analyzed in six studies [46,48,50–52,58], Arthrosis [45,53] and Frailty syndrome [54,57] in two studies, and Dizziness [45], hypertension [45], polypharmacy [45], and spinal cord injury [47] in one study each.

1.4. Structure of the Study

The remainder of this paper is organized as follows: Section 2 presents the methods used for the development of the proposed analysis, including the study design and participants, description of the Timed-Up and Go test, the data acquisition and processing methods used, and the statistical analysis performed in this study. The mobile application developed for data acquisition, the requirements, and the statistical analysis are presented in Section 3. Furthermore, Section 4 offers a discussion on the main findings, limitations, and comparison with our study's prior work. In the end, Section 5 presents the conclusions of this study.

2. Methods

2.1. Study Design and Participants

We selected Android as the operating system for data collection software development as it is open-source software and a market leader. Moreover, we chose the external Bitalino sensors for their appropriate use in research projects in this research domain [59]. This technology could facilitate the creation of significant datasets for health assessment that can be used to support decision-making in medical diagnostics. The mobile device was incorporated in a sports belt to be worn on the waistline. The start of the Timed-Up and Go test was indicated by a sound alarm using the mobile application. The chair incorporated a pressure sensor to register the moment when the older adult re-acted to this sound. The volunteer had to walk for 3 m, go back, and sit down again. All the data were collected on the mobile device, and, after test finalization, a text file was sent to the Cloud by using the FireBase service. Different mobile devices were used for data acquisition to compare the different frequencies of the data acquisition, which verified that the XIAOMI MI 6 was one of the devices that more accurately acquired the different types of data. As the experiments were controlled, we used the same device for final data acquisition and analysis. The data acquisition showed an influence of the environment and varied with the place for data acquisition. It was associated with the study of older adults with different health conditions and ages and resulted in the creation of a dataset with diverse and heterogeneous data.

The data acquired were processed with the Java programming language to extract the different features for the statistical analysis. Firstly, the pressure sensor is used to measure the reaction and total test time. Secondly, the magnetometer sensors are used to extract the total test time, turning around instant by the magnitude of the vector and turning around instant by the absolute value of the z-axis. Finally, the accelerometer sensor is used to extract the reaction time, total test time, duration of turning around, going time, return time, and the averages of the acceleration, velocity, force, and power during going and returning time.

The proposed method was tested on 40 older adults with an age of 60- to 97-years-old (83.8 ± 7.95), privileging gender equality from four institutions, such as Centro Comunitário das Lameiras, Lar Aldeia de Joanes, Lar Minas, Lar da Misericórdia, and others. The “others” corresponds to an open group from different locations. They have several types of health complications, such as Parkinson’s disease, scoliosis, mobility, and cardiovascular problems, and dementia complications (presented in Table A2). The volunteers were institutionalized in nursing homes in the center of Portugal. The selection process was conducted in close collaboration with the nursing team. However, the inclusion criteria relied on mobility capabilities to perform the test. The individuals are randomly selected, and there is no relationship between the individuals and the team of this study. The volunteers were informed about all the specifications and goals of the experiments.

Furthermore, they signed an ethical agreement allowing us to share the results of the tests in an anonymous form. The agreement also provided the participants’ informed consent considering the risks and the objective of the study. Ethics Committee from Escola Superior de Saúde Dr. Lopes Dias at Polytechnic Institute of Castelo Branco approved the study with the number 114/CE-ESALD/2019.

Moreover, other information such as age and weight were provided to support the conclusions of the study. These data were guaranteed to be used in an anonymous form. The data were then measured using a feature extraction method that will be explained in Section 2.2.

Only consistent data were considered in these results. The experiments were held between October and December 2019, and each volunteer underwent the test at three different times. These tests were conducted in an isolated environment to avoid any distractions, which could impact the results. Each institute provided the chair used in the experiments. The volunteers had different health states, some of them still healthy, had diseases related to the spine, such as multiple sclerosis, diseases related to the heart, arrhythmia, or angina pectoris, or illnesses associated with the mental health, such as Parkinson’s. These people had various health statuses and distinct degrees of progress for each disease, which indicated that the population’s health status was variable. Thus, the data collected were heterogeneous.

The mobile application acquired the data from the sensors at intervals of milliseconds, but it was converted to seconds to improve its readability. The collection process started with an audible signal. This sound signal represented the beginning of the data capture, which was recorded in text files and sent over the Internet using the Firebase service. Initially, the data were saved in text files. The accelerometer and magnetometer were tri-axis sensors, represented in four columns in the different files, including timestamps and one column for each axis of the sensors (x, y, and z). Further, the pressure sensor acquired the force performed with the user sitting on the chair. These sensors were complementary for the measurement of the different parameters of the Timed-Up and Go test.

2.2. Description of the Timed-Up and Go Test and Data Acquisition and Processing

The Timed-Up and Go test was developed in 1991 to examine functional mobility in the elderly [60,61]. This test allows the recognition of other different diseases, mainly related to walking activities. It has certain phases where it is possible to obtain different readings and calculations of various features, such as sitting on the chair, lifting from the chair, walking for three meters, reversing the march, walking another three meters toward the chair, and sitting on the chair.

The data acquisition was performed with a mobile device equipped with accelerometer and magnetometer sensors, placed in a belt at the waist of the person, and two Bitalino devices, i.e., one with a pressure sensor placed on the back of the chair, and the other with one ECG and one EEG sensor placed in a belt at the chest of the individual.

Currently, only the data acquired from the pressure sensor and the sensors available in the mobile device are processed. Thus, different calculations are performed, including reaction time, time of the end of data acquisition, the total time of the test, turning instant, turning time, walking time, returning time, the average of the acceleration, speed, force, and power. The measurements of the speed, strength, and power are essential to detect some abnormalities in the actions of older adults.

2.3. Statistical Analysis

After the acquisition of the data from the sensors available in off-the-shelf mobile devices and the sensors connected to the Bitalino device, the data analysis was performed. Firstly, the data acquired by the pressure sensor were processed, extracting the reaction time and the total test time. Secondly, the data obtained by the magnetometer sensor were processed, extracting the start time, the end time, the instant and acceleration value of turning around by the Euclidean norm, and the instant and acceleration value of turning around by the minimum absolute value of the acceleration. Thirdly, the data acquired by the accelerometer sensor were processed, extracting the start, reaction, end, and total test times, the instant and duration of turning around, time of walking the first three meters, time to walk back to the chair, and the mean of the acceleration, velocity, force, and power during the walk for the first three meters and during the walk back to the chair.

After measuring the different variables, a statistical comparison between them was performed, analyzing and comparing the results to the averages of each institution, person, and healthcare disease. Also, descriptive statistics, normality tests, and the detection of outliers were performed. After checking the conditions and making sure we can apply ANOVA, we used it to compare averages between institutions and age groups. Thirdly, the results were analyzed by each disease. The ANOVA test was used for the dependence between the different variables to test the relation between the results obtained and the sample characteristics. ANOVA is a statistical test that allows the discovery of potential differences or relations between different variables useful in testing with the distinct features of human beings [62,63]. It will enable the assessment of possible ties and dependencies between different variables. As the Timed-Up and Go test is a physical test related to people's physical conditions, different variables may be affected.

3. Results

3.1. Data Acquisition with a Mobile Application

The mobile application was developed for Android devices using the Android Studio Integrated Development Environment (IDE). The mobile application has two main functionalities. On the one hand, this mobile application performs a continuous data collection using the built-in magnetometer and accelerometer sensors. The data are collected with a sampling rate of 1 kHz and 16 bits of precision. On the other hand, the mobile application handles the communication technologies required to receive data through Bluetooth from the Bitalino device with a pressure sensor but is also responsible for sending the collected data to the Firebase service for storage. The analysis showed that the mobile devices with embedded sensors provide reliability and automation in the Timed-Up and Go test, unlike traditional measurement methods that require manual measuring.

3.2. Requirements

There are two different types of requirements verified for the performance of the experiments, i.e., one related to the environment and the other to the individual. For the execution of the Timed-Up and Go test, the individual should have the possibility to walk, stand-up, and sit-down on the chair independently. It needs a chair, a tape-measure for the identification of the place related to the three meters to walk, and an adhesive tape to mark the site where the individual should reverse the gait. Also, electrodes to position the EEG and ECG sensors in the individual, an adhesive tape to fix the pressure sensor on the chair, and two sports belts to carry the mobile device and the Bitalino device are used.

3.3. Comparison of Different Acquired Data

There are a few options to measure the turning around instant, which are:

- The minimum value or amount of the magnitude of the vector of the accelerometer, calculated after the reaction time;
- The minimum absolute value of the z-axis of the magnetometer, calculated after the reaction time.

Based on the presented steps for the calculation of the turning around instant, the first moment of mobility, and the start time of the test can be measured by the accelerometer and the pressure sensor.

Incidentally, the analysis performed in this paper includes several values. These are:

- Pressure sensor: reaction time, whole test time;
- Magnetometer: total acquisition time, turning around instant by the magnitude of the vector, turning around moment by the absolute value of *z*-axis;
- Accelerometer: reaction time, total test time, duration of turning around, going time, return time, the average acceleration during going time, the average acceleration during return time, the average velocity during going time, the average speed during return time, the average force during going time, the average force during return time, the average power during going time, the average power during return time;

Next, the presentation of these results by age (Section 3.3.1), by institution (Section 3.3.2), and by disease (Section 3.3.3) will be performed.

3.3.1. Results by Age

After checking the requirements, we used the ANOVA test. We found out that there is no statistically significant difference (alpha = 0.05) between the three age groups for all variables/measurements of interest. Figure 1 shows the mean values for the different age ranges for the reaction time and total test time variables obtained with the pressure sensor. Thus, the results of the F-test, through the respective limited probability associated with the test statistic allowed us to conclude that the average values between the three age groups are statistically equal for the analysis for the magnetometer sensor, such as Pr (F > F-test) = 0.231 > 0.05 for the total test time variable, and Pr (F > F-test) = 0.815 > 0.05 for the reaction time variable. Therefore, we accept the null hypothesis that the averages are statistically equal. Although the averages are statistically equal, it is interesting to note that both for the reaction time and for the total variable test time, it is the younger individuals who have shorter tin

gr *Figure 1. Analysis of reaction time and total test time with pressure sensor by age range.*

needs to be increased in future experiments.

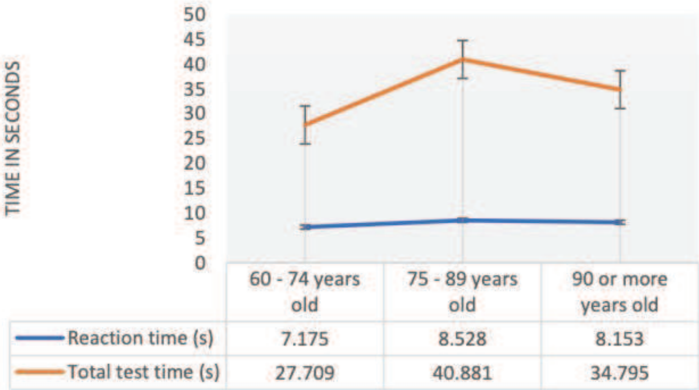

Figure 1. Analysis of reaction time and total test time with pressure sensor by age range.

Then, in Figure 2, we can observe the mean values for the different age range for total test time, turning around instant measured by the magnitude of the vector, and turning around moment measured by the absolute value of z-axis variables obtained with the magnetometer sensor.

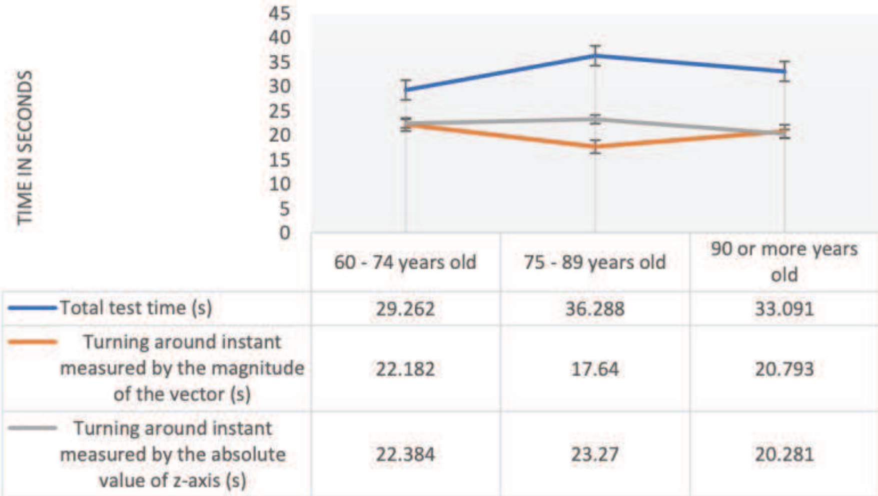

Figure 2. Analysis of total test time, turning around instant measured by the magnitude of the vector and turning around instant measured by the absolute value of the z-axis with the magnetometer sensor by age range.

The results of the ANOVA test, through the respective limit probability associated with the test statistic, allowed us to conclude that the average values between the three age groups are statistically equal for any of the variables under analysis for the magnetometer sensor, namely 32.88 (s) for total test time (Pr (F > F-test) = 0.637 > 0.05), 20.21 (s) for turning around instant measured by the magnitude of the vector Pr (F > F-test) = 0.772 > 0.05, and 20.28 (s) for turning around moment measured by the absolute value of z-axis variables obtained with the magnetometer sensor Pr (F > F-test) = 0.735 > 0.05.

3.3.2. Results by Institution

Aiming to investigate any differences between the participating institutions in this study, we performed a set of ANOVA tests where alpha = 0.5. In cases when there is a statistically significant difference (p < alpha), we applied Tukey's multiple comparison tests to identify homogeneous institutions. For conciseness, we only list the parameters which are statistically significantly different between the institutions (p < alpha).

Namely, the variables with a significant difference in the mean for different institutions are: total test time (s), the conclusion is that there are significant differences between institutions (p-value = 0.03 < alpha = 0.05). The total test time (s) by the pressure sensor, the turning around instant by the absolute value of z-axis (s) by the magnetometer, the total and return test times (s), the averages of velocity during going and returning time (m/s), and the averages of power during going and returning time (J), the total test, going and returning times (s), the average of velocity during return time (m/s), the total test and return times (s), and the averages of velocity and power during going time (m/s) by accelerometer and magnetometer.

Also, we concluded that the average values of all institutions are statistically equal for the reaction time, duration of turning around, the averages of acceleration, velocity, force, and power during going and returning times. The results of this analysis can show that more generic features are statistically equal in different institutions, and therefore might be useful for drawing general conclusions that apply to older adults in general.

3.3.3. Results by Disease

At this stage, approximately 40 different pathologies associated with the subjects were identified. Some individuals have only one pathology, but others have more diseases and from very diverse areas, as shown in Table 1. Of the 40 individuals involved in the study, there are 11 patients with one pathology, nine patients with two pathologies, five patients with three pathologies, five patients with four pathologies, two patients with five pathologies, and only one patient with 6, 7, and 9 pathologies. We can also see the number of individuals identified by pathology and the classification of the respective pathologies by respective categories. This analysis reflects the great diversity of pathologies vs. individuals under study, which may make it difficult and even compromise inferential statistical analysis.

Table 1. Distribution of the different diseases involved in the study.

		Number of Occurrences	Related with Mobility
Osteoarticular diseases (Total of 17 individuals)	Arthrosis	4	Yes
	Scoliosis	2	Yes
	Leg amputation	2	Yes
	Bilateral gonarthrosis	2	Yes
	Osteoarthritis	4	Yes
	Lumbar hernias	1	Yes
	Prosthesis in the right humeral	1	Yes
	Osteoporosis	4	Yes
Cardiovascular diseases (Total of 18 individuals)	Arterial hypertension	16	No
	Cardiac arrhythmia	4	No
	Arteriosclerotic coronary disease	1	No
	Heart failure	5	Yes
	Acute myocardial infarction	1	No
	Chronic Venous Insufficiency of the lower limbs	1	No
Lung diseases (Total of four individuals)	Pulmonary fibrosis	1	No
	Chronic obstructive pulmonary disease	2	Yes
	Chronic bronchitis	2	Yes

Table 1. *Cont.*

		Number of Occurrences	Related with Mobility
Neurological and balance disease (Total of six individuals)	Parkinson	3	Yes
	Dementia	1	Yes
	Chronic headaches	1	No
	Sequelae of surgery to brain injury	1	No
Psychiatric illnesses (Total of six individuals)	Post-traumatic stress	1	No
	Depression	5	No
Nephro-urological disease (Total of nine individuals)	Hypocoagulated	1	No
	Anemia	3	No
	Chronic kidney disease	3	No
	Prostate cancer	4	No
Digestive system and abdominal wall disease (Total of three individuals)	Umbilical hernia	2	No
	Inguinal hernia	1	Yes
	Cirrhosis	1	No
	Gastroenteritis	1	No
Metabolic disorder (Total of 10 individuals)	Hyperuricemia	2	No
	Diabetes mellitus Type II	9	No

Also, it was not possible to read all sensors in the same way for all individuals, resulting in different numbers of samples for the different variables under study. As presented in Table 2, two groups were formed with the pathologies under analysis, including one for diseases directly related to mobility, and others with the other conditions found in the population.

Table 2. Distribution of the different diseases found in the population by its relation to mobility.

Related to Mobility	Not Related to Mobility
	- Arterial hypertension
	- Cardiac arrhythmia
	- Arteriosclerotic coronary disease
- Arthrosis	- Acute myocardial infarction
- Scoliosis	- Chronic Venous Insufficiency of the lower limbs
- Leg amputation	- Pulmonary fibrosis
- Bilateral gonarthrosis	- Chronic headaches
- Osteoarthritis	- Sequelae of surgery to brain injury
- Lumbar hernias	- Post-traumatic stress
- Prosthesis in the right humeral	- Depression
- Osteoporosis	- Chronic anemia
- Heart failure	- Hypocoagulated
- Chronic obstructive pulmonary disease	- Anemia
- Chronic bronchitis	- Chronic kidney disease
- Parkinson	- Prostate cancer
- Dementia	- Umbilical hernia
- Inguinal hernia	- Cirrhosis
	- Gastroenteritis
	- Hyperuricemia
	- Diabetes mellitus Type II

In Figure 3, we can observe the mean and the standard deviation values for reaction time and total test time measured by the pressure sensor by groups of diseases related to mobility and not directly related to movement. Through using the Student's *t*-test to compare two groups of independent samples, it was possible to assess whether there are statistical differences in the level of measurements made between individuals with diseases related to mobility and not associated with movement.

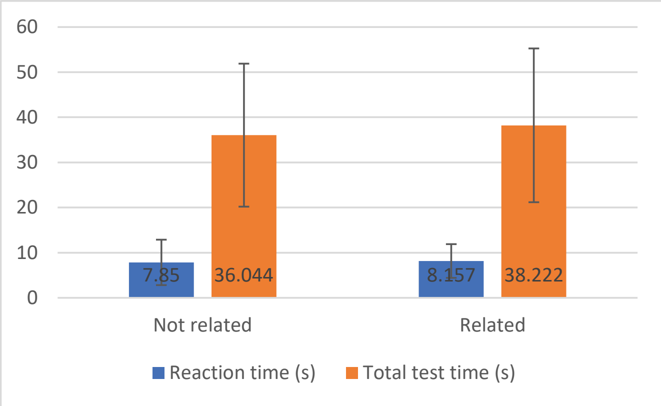

Figure 3. Analysis of reaction time and total test time with a pressure sensor.

First, we concluded the variances are homogeneous (Pr (F > F-test) = 0.079 > 0.05). With the Student's *t*-test, it was possible to conclude that the reaction time (s) between the two groups of diseases not related and related to mobility is equal (Pr (|T| > *t*-test) = 0.838 > 0.05), and the average is statistically similar to 37.133 (s). Hence, it can be said that the 13 individuals with pathologies not related to mobility take less time to perform the test (36.044 vs. 38.222), but this difference is not statistically significant.

Furthermore, the same conclusions can be achieved from the total test time (s) that has identical variances between the groups of diseases not related and related to mobility ((Pr (F > F-test) = 0.960 > 0.05)), and the average is statistically equal (Pr (|T| > *t*-test) = 0.710 > 0.05).

In Figure 4, it is possible to observe the mean values for the total test time (s), turning around instant by the magnitude of the vector (s) and turning around instant by the absolute value of the *z*-axis (s) by magnetometer sensor by diseases related or not related to mobility.

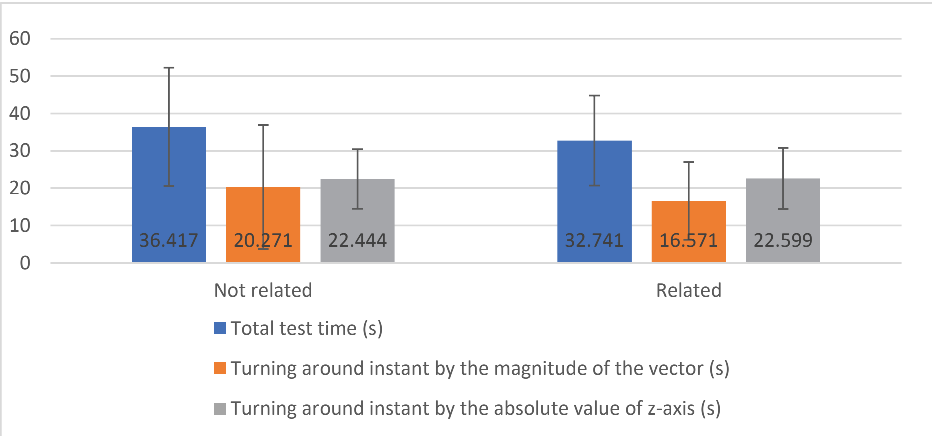

Figure 4. Analysis of total test time turning around instant by the magnitude of the vector and turning around instant by the absolute value of the z-axis with the magnetometer sensor.

With the application of the Student's *t*-test for comparing the variables measured in the magnetometer sensor, by diseases related or not related to mobility, it was concluded that there are no significant differences in measurements between diseases related to mobility and not related to mobility. However, we can verify the following conclusions:

- The total test time (s) has homogeneous variances between the groups of diseases not related and related to mobility (Pr (F > F-test) = 0.459 > 0.05), and the average is statistically equal (Pr (|T| > *t*-test = 0.490 > 0.05);
- The turning around instant by the magnitude of the vector (s) has non-homogeneous variances between the groups of diseases not related and related to mobility (Pr (F > F-test) = 0.029 < 0.05), but the average is statistically equal (Pr (|T| > *t*-test = 0.642 > 0.05);
- The turning around instant by the absolute value of the z-axis (s) has homogeneous variances between the groups of diseases not related and related to mobility (Pr (F > F-test = 0.628 > 0.05), and the average is statistically equal (Pr (|T| > *t*-test = 0.961 > 0.05).

4. Discussion

4.1. Main Findings

The Timed-Up and Go test performed by the elderly population showed a considerable diversity of data because the participants had different types of diseases. The various physical states of each participant in the study demonstrated that the evaluation of the test was reliable with the use of sensors. Thus, the sensors available in the off-the-shelf mobile devices allowed practical data acquisition and further conclusions in real-time. Further, we used a pressure sensor for the reliable detection of the mobility of getting up from the chair. Thus, for additional findings, we extracted several features from the accelerometer and the magnetometer available in off-the-shelf mobile devices, and pressure sensors connected to the Bitalino device.

We anonymously collected the age and different diseases of people to consider during the test's application in older adults. The data were analyzed from different viewpoints, including the measurements by each person, institution, and disease. It was proven that environmental conditions were essential for the reliability of the analysis of the results.

The conditions of the performance of the test, data acquisition, and network connection were adverse in two institutions, namely Lar Aldeia de Joanes and Lar Minas, as presented in Table 3. Considering the measurements performed by the data acquired from the magnetometer sensor, only the data obtained for 32 persons were reliable for further analyses. The relevant report was presented in Table 3. Thus, it is verified that the time measured by the magnetometer sensors was lower than the time measured with the data acquired from the pressure sensor. Considering the measurements performed using the data received from the accelerometer sensor, we concluded that the use of only the accelerometer sensor invalidated some tests in the calculation of the turning around instant. Only 16 persons performed the experiments with reliability, Table 3 presents the data. However, fusing these data with the measurements performed by the magnetometer sensor and using the turning around moment measured by the magnitude of the vector, we found that 22 persons performed the experiments with reliability. By using the turning around instant measured by the absolute value of the *z*-axis, we found that 33 persons performed the examinations successfully. Considering the measurements performed using the data acquired from the accelerometer sensor, we found that the use of only the accelerometer sensor invalidated some tests in terms of the calculation of the turning around instant. Thus, only three institutions performed the experiments with reliability, and only people with nine diseases were analyzed. However, fusing these data with the measurements performed by the magnetometer sensor, we concluded that the six institutions performed the experiments with reliability. Therefore, we find that the return time was higher than the going time with higher acceleration, velocity, force, and power during the return time. Thus, we concluded that the return time was higher than the going time with higher acceleration, velocity, force, and power during the return time. With the fusing of these data with the measurements performed by the magnetometer sensor and using the turning around moment measured by the magnitude of the vector, we analyzed 16 diseases. Using the turning-around instant measured using the absolute value of the *z*-axis, we analyzed 27 illnesses.

Table 3. Relation between sensors and results obtained.

Sensors	Parameters	Analysis		
		By Age	**By Institution**	**By Diseases**
Pressure sensor	Reaction time	-	It is higher in Lar Aldeia de Joanes and Lar Minas (14.860 s), and lower in Lar Nossa Senhora de Fátima (5.948 s)	It is higher in persons with sequelae of surgery to brain injury (16.830 s), and lower in persons with pulmonary fibrosis, acute myocardial infarction, and hypocoagulated (3.477 s)
	Total test time	It is lower in an individual of 60-years-old with scoliosis (21.070 s)	-	It is higher in an individual with a leg amputation and diabetes mellitus Type II (92.950 s).
Magnetometer sensor	Total test time	It is lower in an individual of 60-years-old with scoliosis (19.761 s)	It is lower in Centro Comunitário das Lameiras (28.778 s), and higher in institutions with poor conditions (74.053 s)	It is higher in people with osteoarticular pathology and a prosthesis in the right humeral (66.947 s), and lower in people with arthrosis (24.528 s)
	Turnaround measured by the magnitude of the vector	The time is higher in an individual of 89-years-old with problems related to mobility (51.742 s)	The instant is lower in Lar da Misericórdia (2.591 s)	The instance is higher in people with congestive heart failure (28.886 s), and lower in people with osteoarticular pathology and prosthesis in the right humeral (3.836 s), and the time is higher in people with lumbar hernias and a gastric ulcer (30.643 s)
	Turning around instant measured by the absolute value of the *z*-axis	It is higher in participants with osteoarthritis of 87-years-old (39.649 s).	It is lower in Centro Comunitário das Lameiras (8.433 s), and it is higher in Lar Nossa Senhora de Fátima (39.649 s).	It is lower in people with osteoarticular pathology and a prosthesis in the right humeral (8.704 s), and it is higher in people with osteoarthritis (39.649 s)
Accelerometer sensor	Times	Average of 10.521 s in reaction time, 45.538 s in total test time, 13.272 s in going time, and 21.944 s in return time		
	Turning around	In average, the duration is 0.436 s, and the instant is 23.566 s		
	Acceleration	Average of 9.96 m/s^2 in going time, and −11.43 m/s^2 in return time.		
	Velocity	Average of 15.12 m/s in going time, and −5.51 m/s in return time.		
	Force	Average of 713.37 N in going time, and −1886.03 N in return time.		
	Power	Average of 6233.21 J in going time, and −8491.09 J in return time.		

Some individuals reported an inconsistency between the different diseases and the results obtained by the values acquired using the various sensors, and this inconsistency could be attributed to the adverse conditions of the data acquisition. In general, older adults have more than one disease. Still, the best results obtained with the magnetometer were obtained in people with arthrosis disease, where the person only has arthrosis, and the other people have several diseases. The same problem was observed in the case of people with osteoarticular pathology, and prosthesis in the right humeral, where the going time was lower than that for the other people. In conclusion, the sensors might report bad data, and the findings might be argued. The other problem was that people with osteoarticular pathology and prostheses in the right humeral reported better results in the measurement of turning around than people with lumbar hernias and gastric ulcers. They were attributed to the fact that people with gastric ulcers had more than one disease, and people with several diseases reported higher times than the others.

To ensure that these data collection methodologies can be used to assess physical and functional performance in the clinic, this data should be valid, reliable, and with proper responsiveness, as has been demonstrated by the Timed-Up and Go test in a variety of conditions [64,65].

4.2. Limitations

As presented in Table 4, there are three possible origins of limitations found, such as individuals, environment, and technical. The older adults and environments for the different tests are heterogeneous. However, other technical barriers related to the Internet and Bluetooth connection availability, and synchronization between the various devices were found. The individuals performed the examination three consecutive times to avoid some problems, and the acquisition started at the same time in all devices.

Table 4. Relation between the origin and limitations of the study.

Origin	Limitation
Individuals	Different health conditions.
Environment	The experiments were performed in uncontrolled environments.
Technical	The Internet connecting is needed for data synchronization.
	Bluetooth connected reported some failures.
	A large volume of data needs to be processed in the mobile device.
	Data cannot be processed in real-time.
	Sometimes it was not possible to consistently synchronize the timestamps of the acquired data, because Bitalino does not have real timestamps.

4.3. Comparison with Prior Work

Different studies analyzed the performance of the Timed-Up and Go test with sensors to measure the various parameters. Still, only two studies [45,50] show the values of the measured parameters. These studies are not comparable with the values obtained in our study, because they only calculate the power. There are multiple literature surveys of the Timed-Up and Go test [60,64,66], but they do not explicitly consider the inclusion of older adults. It is also evident because of the discrepancy in the reported values of high power, which is uncommon for older adults who usually have low energy. As the people of other studies are younger, the power/energy used to perform the Timed-Up and Go test is higher than in our research, reporting −28,934.32 J. However, it depends on the health diseases and age of older adults in the study. The age range of participants in our study is higher than the studies available in the literature.

Among the other approaches that use mobile devices for automation of the Timed-Up and Go text, the most prominent ones are [32,45,49,67]. Similarly, our study also measures the duration of the Timed-Up and Go test and identify the different stages. Unlike them, our study is mainly performed by older adults, uses multiple sensors to monitor the various movements, and measures parameters including power, velocity, acceleration, force, reaction time, and others, to measure the performance of the test more accurately. The main differences and advantages of our study are presented in Table 5.

Table 5. Comparison of the studies in the literature with our study.

Study	Differences Compared to Our Study	Advantages of Our Study
[45]	The study is related to the fall risk assessment, and our research is associated with the analysis of the performance of the Timed-Up and Go test for the creation of patterns by age, disease, and institution.	Our study proved that a relation between diseases related to mobility and the performance of the Timed-Up and Go test exists, allowing the creation of different patterns with the inertial sensors.
[49]	The study identified the different phases of Timed-Up and Go sensors. The authors also calculated the Minimal Detectable Change based on the speed, where we identified the various stages, and measured the force, power, and acceleration of the movement.	The older adults sometimes performed more force and power than the other population. The measurement of these parameters is vital to identify the reliability of the test in the different repetitions.
[32]	The study tracks the different stages of the Timed-Up and Go test, and the angles of the knee and ankle. Our study identified the different phases and made other measurements.	Our study is focused on older adults that commonly have different pathologies, performing different measurements and relationships between diseases.
[67]	The authors implemented machine learning methods for the distribution of the individuals in different groups to cluster the types of diseases.	Our study performed the analysis of the different features extracted with a focus on the diseases related to the movement.

5. Conclusions

The Timed-Up and Go test is an easy test used to measure different types of mobility. This study considered performed the analysis of older adults. This test consists of the individual sitting on the chair, getting up from the chair, walking three meters, reversing the direction of the walking, walking another three meters to back to the chair, and sitting on the chair.

The automatic measurement of the Timed-Up and Go test with mobile devices is possible, validating the different parts of the test. This work considers the data acquired from the various sensors available in the mobile device, including the accelerometer and magnetometer sensors, where the magnetometer sensors help in the detection of the changes of the direction during the test, where the accelerometer sensors allow the measurement of the acceleration, velocity, force, and power. A Bitalino device with a pressure sensor in the chair is used to detect the mobility's start. Another Bitalino device was used to acquire the electrocardiography (ECG) and electroencephalography (EEG) for future processing.

This work aimed to analyze the data obtained in different elderly institutions with various conditions. It was verified that data acquisition conditions influenced data acquisition. The different diseases of the individuals also affect the results of the performance of the Timed-Up and Go test. Through the automatic calculation of the features, different values were obtained. Thus, various analyses were carried out by age, institution, and type of disease, which allowed the measurement of exciting results. It was verified that this study allows the possibility to create different patterns of physical states of people. However, several constraints may have influenced the experiment's results, including the test environment and the reception conditions of the network. The data are somewhat heterogeneous because we are analyzing older adults with different health conditions. The statistical grouping by different age ranges allows us to show the influence that age may have on the test results. The Timed-Up and Go test has been demonstrated to be an accessible and clinically relevant test to assess mobility, balance, and risk of falls in the elderly and other populations with health problems.

With the rise of chronic health conditions, it is fundamental to create accessible, valid, and reliable online instruments that evaluate and record physical health performance, like the Timed-Up and Go test. It is also vital to guarantee that the follow up gives a real evolution of this performance with some health treatments, such as physiotherapy. Future work may recognize different diseases with the values acquired during the experiments, considering the ECG and EEG sensors. The values obtained with the ECG sensor allow for the detection of dysrhythmias, ischemia, driving disorders, ST-segment abnormality, cavity overload, pericarditis, pericardial effusions, ion disorders, and congenital heart diseases. On the other hand, the values obtained with the EEG sensor allows the detection of convulsions, metabolic encephalopathies, structural encephalopathies, degenerative diseases, infections, sleep disorders, and memory changes.

This pilot study proved to be a great way to help diagnose different types of diseases, whether they involve the individual's motor capacity, whether cardiac or neurological. In the future, the use of low-cost systems and mobile sensors may help an evolution in medicine for the diagnostics of different diseases in people.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

This section presents Table A1 related to the features extracted in different studies. Also, it presents Table A2 related to the description of the population of the study.

Table A1. Studies vs. Features extracted.

Features	Studies	Number of Studies
Duration of the test	[17,32,49,51,52,54,55,58]	8
Maximum	[17,45,56–58]	5
Mean	[46,49,54,56,58]	5
Duration of each stage	[17,47,50,51,56]	5
Root Mean Square (RMS)	[45,46,56,58]	4
Standard deviation	[45,46,56,58]	4
Velocity	[32,44]	2
Time of sit-to-stand transition	[44,48]	2
Minimum	[45,57]	2
Energy	[45,46]	2
Entropy	[45,46]	2
Mobility angles	[32,48]	2
Time of stand-to-sit	[53,55]	2
Time of prepare-to-sit	[53,55]	2
Time of sit-down	[53,55]	2
Time of lift-up	[53,55]	2
Maximum change of the trunk angle	[51,55]	2
Maximum angular velocity during the lean forward and lift-up phases	[51,55]	2
Median deviation	[45]	1

Table A1. *Cont.*

Features	Studies	Number of Studies
Skewness	[45]	1
Interquartile range (IQR)	[45]	1
Kurtosis	[45]	1
Maximum and second maximum frequencies and amplitudes of the Fast Fourier Transform (FFT)	[45]	1
Number of times that the amplitude of the magnitude of the vector of accelerometer signal crosses the mean value	[45]	1
Mean of peak height	[45]	1
Correlation	[46]	1
Pitch	[46]	1
Signal Magnitude Area (SMA)	[46]	1
Signal Vector Magnitude (SVM)	[46]	1
Angular velocity of the mobility of the arm	[50]	1
Time to perform turn-to-sit	[50]	1
Time of lean forward phase	[53]	1
Time of the walking phase	[53]	1
Maximum angular velocities during lean forward and lift-up phases	[53]	1
Maximum change of trunk angle during the lean forward phase	[53]	1
Total number of steps during the walking phase and before the turn	[53]	1
Stride length	[32]	1
Distance traveled	[32]	1
Length of the lean forward period	[55]	1
Number of steps during	[55]	1
Coefficient of variation	[56]	1
Jerk	[58]	1

Table A2. Description of the population of the study and test conditions.

Institution	Person ID	Diseases	Diseases Related to Mobility	Age (Years)	Test Conditions
Centro Comunitário das Lameiras	1	Arthrosis	Yes	85	Chair without supports. Spacious place. Floor with the right conditions. Good mobile network coverage. A physical therapist monitored the test.
Centro Comunitário das Lameiras	2	Gastroenteritis	No	92	
Centro Comunitário das Lameiras	3	Arterial hypertension; Arthrosis	Yes	85	
Centro Comunitário das Lameiras	4	Arterial hypertension; Cardiac arrhythmia	No	92	
Centro Comunitário das Lameiras	5	Arterial hypertension; Cardiac arrhythmia; Diabetes mellitus Type II; Scoliosis	Yes	92	
Centro Comunitário das Lameiras	6	Scoliosis	Yes	85	
Centro Comunitário das Lameiras	7	Osteoporosis	Yes	83	
Centro Comunitário das Lameiras	8	Arthrosis	Yes	87	

Table A2. *Cont.*

Institution	Person ID	Diseases	Diseases Related to Mobility	Age (Years)	Test Conditions
Others	9	Scoliosis	Yes	60	Excellent quality of mobile network coverage. Tight space in the kitchen. Chair with supports.
Others	10	Right leg amputation; Diabetes mellitus Type II	Yes	77	
Lar Aldeia de Joanes	11	N/D	-	N/D	Weak mobile network coverage. Test site with the right physical conditions. The test was carried out in a place with other older adults. Chair with supports.
Lar Minas	12	Arterial hypertension	No	88	Mobile network coverage does not exist. Test site with Good physical condition of the test site. The test was carried out in a living room with other older adults. Chair with supports.
Lar Minas	13	Arterial hypertension; Cardiac arrhythmia; Arteriosclerotic coronary disease; Heart failure	No	84	
Lar Minas	14	N/D	-	65	
Lar da Misericórdia	15	N/D	-	91	The basement of a building with little mobile network coverage. Chair with supports. Flat ground with a slight slope.
Lar da Misericórdia	16	N/D	-	84	
Lar da Misericórdia	17	Hernioplasty in 2010; Sarcoidosis	No	87	
Lar da Misericórdia	18	Chronic obstructive pulmonary disease; Chronic bronchitis; Osteoarthritis	Yes	73	
Lar da Misericórdia	19	Cirrhosis; Anemia; Chronic kidney disease; Umbilical hernia; Inguinal hernia	Yes	79	
Lar da Misericórdia	20	Right leg amputation; Umbilical hernia; Arterial hypertension	Yes	88	
Lar da Misericórdia	21	Prostate Cancer; Parkinson's disease; Post-traumatic stress	Yes	76	
Lar da Misericórdia	22	Arterial hypertension; Diabetes mellitus Type II	No	86	
Lar da Misericórdia	23	Prostate Cancer; Osteoporosis; Chronic Venous Insufficiency of the lower limbs; Chronic bronchitis	Yes	92	
Lar da Misericórdia	24	Diabetes mellitus Type II; Arterial hypertension; Depression; Sequelae of surgery to brain injury	No	83	
Lar da Misericórdia	25	Diabetes mellitus Type II; Vertigo syndrome; Chronic headaches; Osteoarthritis; Prosthesis in the right humeral; Osteoporosis; Arterial hypertension	Yes	81	
Lar da Misericórdia	26	Arterial hypertension; Anemia	No	91	
Lar da Misericórdia	27	Osteoarthritis; Depression; Heart failure; Arterial hypertension; Osteoporosis	Yes	89	
Lar da Misericórdia	28	N/D	-	N/D	

Table A2. *Cont.*

Institution	Person ID	Diseases	Diseases Related to Mobility	Age (Years)	Test Conditions
Lar da Nossa Senhora de Fátima	29	Diabetes mellitus Type II;	No	86	The test location was narrow. The mobile network coverage was of good quality. The floor and width of the test site were very tight. The chair had no supports.
Lar da nossa senhora de Fátima	30	Dementia of vascular etiology; Prostate Cancer; Arterial hypertension; Vertigo syndrome	Yes	N/D	
Lar da nossa senhora de Fátima	31	Depression; Osteoporosis	Yes	83	
Lar da Nossa Senhora de Fátima	32	Diabetes mellitus Type II; Osteoarthritis	Yes	87	
Lar da Nossa Senhora de Fátima	33	Diabetes mellitus Type II; Arterial hypertension; Heart failure; Hyperuricemia; Depression; Bilateral gonarthrosis	Yes	N/D	
Lar da nossa senhora de Fátima	34	Prostate cancer	No	88	
Lar da Nossa Senhora de Fátima	35	Heart failure; Chronic obstructive pulmonary disease; Bilateral gonarthrosis	Yes	97	
Lar da nossa senhora de Fátima	36	Diabetes mellitus Type II; Arterial hypertension	No	71	
Lar da nossa senhora de Fátima	37	Arterial hypertension	No	74	
Lar da Nossa Senhora de Fátima	38	Osteoarthritis; Lumbar hernias; Depression; Gastric ulcer	Yes	82	
Lar da Nossa Senhora de Fátima	39	Heart failure; Arterial hypertension; Pulmonary fibrosis; Hyperuricemia; Anemia; Chronic kidney disease; Cardiac arrhythmia; Acute myocardial infarction; Hypocoagulated	Yes	N/D	
Lar da nossa senhora de Fátima	40	Chronic kidney disease	No	90	

N/D: The values were not reported by the older adults.

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4.2. Experimental Study for Determining the Parameters Required for Detecting ECG and EEG Related Diseases during the Timed-Up and Go Test

The following article is the second part of the chapter 4.

Experimental Study for Determining the Parameters Required for Detecting ECG and EEG Related Diseases during the Timed-Up and Go Test

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Experimental Study for Determining the Parameters Required for Detecting ECG and EEG Related Diseases during the Timed-Up and Go Test

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Abstract: The use of smartphones, coupled with different sensors, makes it an attractive solution for measuring different physical and physiological features, allowing for the monitoring of various parameters and even identifying some diseases. The BITalino device allows the use of different sensors, including Electroencephalography (EEG) and Electrocardiography (ECG) sensors, to study different health parameters. With these devices, the acquisition of signals is straightforward, and it is possible to connect them using a Bluetooth connection. With the acquired data, it is possible to measure parameters such as calculating the QRS complex and its variation with ECG data to control the individual's heartbeat. Similarly, by using the EEG sensor, one could analyze the individual's brain activity and frequency. The purpose of this paper is to present a method for recognition of the diseases related to ECG and EEG data, with sensors available in off-the-shelf mobile devices and sensors connected to a BITalino device. The data were collected during the elderly's experiences, performing the Timed-Up and Go test, and the different diseases found in the sample in the study. The data were analyzed, and the following features were extracted from the ECG, including heart rate, linear heart rate variability, the average QRS interval, the average R-R interval, and the average R-S interval, and the EEG, including frequency and variability. Finally, the diseases are correlated with different parameters, proving that there are relations between the individuals and the different health conditions.

Keywords: diseases; electrocardiography; electroencephalography; timed-up and go test; sensors; mobile devices; feature detection; diseases; older adults

1. Introduction

1.1. Background

Currently, the world's population is increasingly aging, promoting research in several medical areas [1]. Due to the increase in life expectancy, the research studies focused on the elderly population are essential to improve the quality of life of the elderly. There are 157 elderly persons per hundred young people, so we can verify that the number of older adults is around 64% higher than young people [2–5]. Commonly, older adults have different types of pathologies. The automatic identification of these diseases based on the data acquired during the Timed-Up and Go test may allow different preliminary treatments [5–7]. The future generation of older adults will use mobile devices intensively [8,9], allowing the possibility of recognizing different types of diseases with these devices [10–15]. The evolution and high proliferation of the technological equipment with varying kinds of sensors allow the growth of the development of novel medical solutions [16], promoting the elderly to independent living with remote medical control [17].

Several sensors are embedded in mobile devices, but other sensors may be used in conjunction with the internal sensors to provide different measurements related to various physical and physiological parameters [18,19]. Regarding the analysis of different variables of the Timed-Up and Go test, the accelerometer and magnetometer sensors embedded on mobile devices may be used in conjunction with external sensors to perform complementary measurements [20–22].

Previous works show that the accelerometer and magnetometer sensors may support the analysis of the individuals' functionality, including the gait [23,24]. However, one of the significant problems in this type of study consists in the synchronization of the acquisition of the different types of data from the sensors embedded on mobile devices, and the other sensors connected by over-the-air connection, including Electrocardiography (ECG) and Electroencephalography sensors (EEG) [25–29]. In addition to this challenge, data processing may include the fusion of the data acquired from different sources.

One of the most common tests for the assessment of the performance of the lower limbs is the Timed-Up and Go test, where the analysis of the data acquired from different sources allows the recognition of several healthcare problems, including balance, mobility, fall risk, Parkinson's disease, amyotrophic lateral sclerosis, and other orthopedic, cardiovascular and brain pathologies [30–35].

The use of ECG and EEG sensors in conjunction with Timed-Up and Go tests allows cardiac problems and other problems associated with the nervous system to be monitored for the first analysis of emergency [25–29]. One of the low-cost solutions that may be used in conjunction with mobile devices is the BITalino device and its sensors [36]. The BITalino device is an example of biomedical equipment that is scalable and versatile, used for the acquisition of different biosignals transmitted by Bluetooth. The ECG sensors detect the duration and variation in size of the ECG waves used for the abnormalities of heart rate. Furthermore, the EEG sensor is used for the capture of the brain activity and it is positioned in a bipolar configuration with two measurement electrodes for the detection of electrical potentials. Combining smartphones with these devices and sensors may allow for the acquisition of cardiac signals, realizing the relationship of these signals with diseases associated with the heart, and the recognition of different healthcare problems.

In this work, we build upon previous studies [37,38] related to the acquisition of data from the accelerometer and magnetometer sensors available on the off-the-shelf mobile devices, pressure sensors available in the back of the chair, and ECG and EEG sensors, for the detection of different types of movement, and cardiac and brain problems. This paper aims to design and develop a method for the acquisition, analysis, and identification of different patterns of diseases with low-cost sensors. To facilitate this, the proposed solution uses embedded smartphone sensors and additional ones connected to a BITalino device [36] to identify patterns in measured ECG and EEG signals during Timed-Up and Go test and find their relation to existing illnesses of patients. We show that such correlation exists and that it can be used to identify emerging medical conditions, so they can be treated from early on.

1.2. Motivation

This research is supported by the ability to accurately identify various parameters during the Timed-Up and Go test [39]. However, the use of mobile devices to help the capture of the various sensors poses several additional restrictions associated with the memory, power processing, among others [40,41]. The data captured during the Timed-Up and Go test are essential for further measurements, where we intend to create a large dataset from different sensors used for additional measures of various diagnostics in medicine.

Different diseases may be recognized by the use of the Timed-Up and Go test [42], allowing healthcare professionals to assess different healthcare conditions of older adults. This implementation may be first aid or preliminary detection of various diseases in an initial state [43]. As it is an easy test, it may be performed with people with neurological disorders [44], allowing the pattern recognition of different diseases. Several parameters may be measured for the detection of cardiac diseases, including the heart rate, linear heart rate variability, the amplitude of complex QRS, and amplitudes of R-R and R-S intervals, for the detection of different diseases.

1.3. Prior Work

The ECG and EEG signals have been used in the past for the recognition of different diseases. The authors of [45] filtered the acquired ECG data and applied a differential transfer function to the signal. The authors of [45] also squared the ECG signal to obtain information about the waveform and to calculate the heart rate. According to the authors of [45], a heart rate below 60 bpm is related to the presence of a bradycardia disease. A tachycardia is identified with a heart rate higher than 100 bpm. In continuation, the premature ventricular contraction is recognized for an amplitude of the QRS complex higher than 120 ms [45]. Bradycardia and tachycardia diseases are not identified, but the heart rate is not between 60 and 100 bpm, the premature atrial contraction may be recognized [45].

The detection of different diseases, including normal sinus rhythm, premature atrial beat, atrial fibrillation, supraventricular tachyarrhythmia, pre-excitation, premature ventricular contraction, ventricular bulge, ventricular triplet, ventricular tachycardia, idioventricular rhythm, fusion ventricular block beat of the left branch, block beat of the right branch, were recognized with neural networks with features related to the normalization, maximum pooling, flattening, density, among others, related to several sliding windows [46]. The measurement of the P-R interval and the amplitude of QRS were also used for the recognition of cardiovascular death [47].

In [48], the authors recognized primary and secondary pulmonary hypertension with the amplitude of the P wave in the II derivation, the frontal mid axis of the QRS complex, duration of the QRS complex, deviations of the R and S waves in leads I and V6 and the T wave configurations in the precordial leads, where the best correlation was obtained with the value of the frontal mid-axis of the QRS complex.

The authors of [49] developed a method to detect atrial fibrillation based on the absence of P wave, irregular heart rate, and other variables related to the atrial activity. The implementation of the Pan Tompkins algorithm was used to detect arrhythmias with features related to frequency and time domains [50]. The detection of the coronary artery disease was recognized by the amplitude of QRS interval, and depressions S-T and T wave [51].

With the use of neural networks, the authors of [52,53] also detected various cardiac diseases, including left bundle branch block, right bundle branch block, premature ventricular contraction, Wolff–Parkinson–White syndrome, myocardial ischemia, and myocardial injury, with the duration of P, S, T and QRS, P-R and Q-T intervals, P, R and T amplitudes, and S-T segment.

Parkinson's disease may be detected with different features, including R-R, P-R, QRS, and Q-T intervals, and the heart rate measured and corrected by Q-T interval, analyzing the Spearman correlation coefficient [54]. Based on different features, including heart rate, P, T and QRS intervals, P durations, and P-R, QRS, Q-T and corrected Q-T intervals, ventricular activation time, and frontal plane axis, the authors of [55] recognized left and right ventricular hypertrophies.

Related to the EEG signal, the authors of [56] implemented machine learning methods for the recognition of various diseases, including Alzheimer's disease, with different statistical, amplitude, and frequency-based features. On the other hand, the authors of [57] implemented machine learning methods with time–domain features. Epilepsy is detected by various studies with machine learning methods, including Support Vector Machine (SVM), adaptive neuro-fuzzy inference system, and linear classifier, based on different features based on wavelet coefficients, including 2nd order cumulants (mean ± standard deviation), asymmetry, kurtosis, spectral, Renvi, Kolmogorov–Sinai, variance, energy, and the maximum and minimum values of the power spectral density [58–61].

Based on signal strength, window strength, and sample entropy, Alzheimer's disease is correctly recognized with linear discriminant analysis [62]. Finally, acute ischemic stroke is detected by the densities of the power spectrum acquired by different devices [63]. As presented in Table 1, the diseases recognized by the ECG and EEG sensors are distributed by the number of the studies analyzed.

Table 1. Studies vs. Diseases.

Diseases	Studies	Number of Studies
ECG		
Arrhythmia (i.e., atrial fibrillation, supraventricular tachyarrhythmia, pre-excitation, ventricular tachycardia, idioventricular rhythm, left and right branch block, and Wolff–Parkinson–White syndrome)	[46,49,50,53]	4
Premature ventricular contraction	[45,46,53]	3
Primary and secondary pulmonary hypertension; coronary artery disease; myocardial ischemia; myocardial injury; Parkinson's disease; left and right ventricular hypertrophies	[48,51,53–55]	1
EEG		
Epilepsy	[58–61]	4
Alzheimer's disease	[56,62]	2
Brain abnormalities; acute ischemic stroke.	[63]	1

1.4. Purpose of the Study

The hypothesis of this research is that Android smartphones complemented by affordable external ECG and EEG sensors can provide a reliable method for the identification of different diseases. In particular, the paper aims to identify the different waves from the ECG and EEG sensors, calculate various metrics based on them, and verify that each disease has distinct features that can facilitate its identification.

The presentation of a method for recognizing the diseases related to ECG and EEG data with sensors, available in off-the-shelf mobile devices, and sensors connected to a BITalino device during the performance of the Timed-Up and Go test is the main contribution of this paper. This document presents the measurement of different features to create a reliable dataset for the recognition of the various diseases present in the sample in analysis. Additionally, this paper presents a state-of-the-art review of the methods used in the literature to identify illnesses related to ECG and EEG signals. The use of mobile devices proves its usability in these types of studies.

The data were previously acquired from people aged between 60 and 97 years old with several diseases. Clinicians already identified the disorders of each participant for the success of this study related to automatic identification, including arterial hypertension, depression, cardiac arrhythmia, coronary artery disease, and Parkinson's disease. These diseases are only recognized with ECG sensors, where the EEG sensor is only used to detect possible abnormalities. The data acquisition was performed by institutionalized people in the Centre region of Portugal, explicitly in the municipalities of Fundão and Covilhã.

The data acquisition was performed during the performance of the Timed-Up and Go test with Android devices. The accelerometer and magnetometer data from the embedded sensors feature on the mobile device, pressure sensor data are placed on the back of the chair, and the EEG and ECG sensors are connected to the individual for the data acquisition. The mobile application simultaneous acquire the data from the different sensors, where, after data acquisition, the various text files were uploaded to the Cloud by using the FireBase service.

Commonly, ECG and EEG data are captured while the subject is stationary. Contrary to that, The Timed-Up and Go test involves movement. Be that as it may, there are approaches such as [63] which show that, even in cases when the subject is moving, recognition of different diseases related to ECG and EEG data [64] is still possible. This would be convenient for the users to perform these measurements while having light movement during other tests. Moreover, there also be some advantages to this approach because it can emphasize some emerging medical conditions that may become more apparent during movement. This subject is related to Internal Medicine, and the recognition of different diseases in an early stage is excellent for the treatment of different diseases [65,66].

After the data acquisition, the ECG and EEG data were processed, and the different features were extracted. The features extracted from the ECG sensors were the heart rate, the linear heart rate variability, the average QRS interval, the average R-R interval, and the average R-S interval. Next, the features extracted from the EEG sensor were frequency and variability.

The different features were correlated with the institutions, and the diseases present in the sample. Initially, the correlation between the values extracted from the sample and the diseases identified by the healthcare professionals was performed, verifying that they are commonly determined by different parameters, except the coronary artery disease and bilateral gonarthrosis. Applying different statistical tests, we also proved different correlations between diseases, and parameters extracted, as presented in Section 4.1.

1.5. Structure of the Study

The remaining sections of this paper are organized as follows: Section 2 presents the methods used for the analysis of the data acquired from ECG and EEG sensors during the performance of the Timed-Up and Go test by older adults. The study design and participants' description of the Timed-Up and Go test, the data processing and acquisition processing, and the statistical analysis are presented in Section 3. In continuation, Section 4 discusses the main findings and limitations of the study. The comparison with prior work is also shown in Section 4. Finally, the conclusions of this study are presented in Section 5.

2. Methods

2.1. Study Design and Participants

For the acquisition of data related to the Timed-Up and Go test, this study is designed to use one mobile device with accelerometer and magnetometer sensors, and two BITalino devices with pressure, ECG, and EEG sensors. The mobile device is used for data acquisition and to send the collected data to the server. Several environments may be recognized, but our focus is related to healthcare. This study is a trial to check if, during the performance of the test, we can identify different types of diseases.

This study's target is related to the population with cardiac and brain problems institutionalized in retirement homes and aged between 60 and 90 years. The sample for the analysis was selected in collaboration with the people responsible in the retirement homes. The requirement is related to the possibility of having mobility capabilities to perform the test. The volunteers were informed of all the rules to complete the test and the instrumentation. They signed the ethical agreement to publish the results of the experiments in an anonymous form.

The tests were performed with a XIAOMI MI6 with the Android operating system, but the different environment variables vary between the various institutions, which influences the data acquisition. The different individuals performed the test between October and December 2019 several times. Initially, the test was performed by 40 older adults, however, due to the over-the-air connection constraints, the ECG and EEG signals were only reliable acquired from 14 individuals with mean age 83.1 and a standard deviation of 7.4. The various healthcare diseases were presented in Table 2. The different volunteers have different types of diseases, including multiple sclerosis, diseases related to the heart, such as arrhythmia, or illnesses associated with mental health, such as Parkinson's disease. Of the participants, 50% had a chair with supports and also 50% of them had good mobile network coverage. Only 14% of the patients were monitored by a physical therapist. The physical condition of 14% was good, 43% were narrow and tight, and 43% had a slope. Thus, the acquired data are heterogeneous. Parkinson's disease is commonly classified as an illness related to mental health, but the derivations of ECG sensors frequently detect it.

The sample selected has different cardiac and brain problems that result in the creation of a dataset with varying types of data that will be processed, as presented in Section 2.2. The essential diseases analyzed were arterial hypertension, depression, cardiac arrhythmia, coronary artery disease, and Parkinson's disease. The mobile application acquired the data from different sensors with different delays. The accelerometer and magnetometer sensors receive the data every 1 ms, and the pressure, ECG, and EEG sensors acquire the data every 10 ms. The EEG and ECG values taken into account in this study are related to the alpha channel of the sensor. The electrodes of the EEG sensors were placed in the electrically neutral location (left) and measurement electrodes (right), and another electrode in a region of low muscular activity as reference. The two electrodes of ECG sensor were placed at the wrist of the individual. The ECG and EEG sensors connected to the BITalino device has only one channel for the acquisition of the data [36]. The data acquisition process starts with an acoustic signal, which signals the start of the data acquisition.

2.2. Description of the Timed-Up and Go Test and Data Acquisition and Processing

In 1991, the Timed-Up and Go was created to help the healthcare professionals for the measurement of the risk of falls [60]. The Timed-Up and Go test is composed of various phases: sitting on the chair, lifting from the chair, walking for three meters, reversing the direction of walking, walking another three meters towards the chair, and sitting on the chair.

During the test's performance, some technical issues influence the acquisition of signals by the BITalino device, such as the failure of the sensors data acquisition, the Bluetooth connection is lost, among others. This makes it more complicated to perform realistic studies on the field with actual patients, therefore the number of valid data points was reduced. The acquisition of different types of data was performed with a mobile device and two BITalino devices. The sensors used for the measurement of the results of the test and other complementary sensors may be used for the analysis of different parameters of healthcare diseases.

2.3. Statistical Analysis

After the acquisition of the data from the sensors, available in off-the-shelf mobile devices, and the sensors connected to the BITalino device, the data analysis was performed. The main goal is to analyze the data acquired from the ECG and EEG sensors during the performance of the Timed-Up and Go test for helping in recognition of the diseases associated with these sensors. Firstly, the ECG data were processed for the extraction of heart rate, linear heart rate variability, the average of QRS interval, the average of R-R interval, and the average of R-S interval. Finally, the EEG sensor as processed for the extraction of its frequency and variability.

After measuring the different variables, descriptive statistics, normality tests, and detection of outliers were performed. In addition, a statistical comparison between them was performed, analyzing and comparing the results by the averages of each institution, person, age, and healthcare diseases.

Table 2. Description of the population of the study and test conditions.

Person ID	Diseases	Age (Years Old)	Test Conditions			
			Chair with Supports	Good Mobile Network Coverage	Physical Conditions	Monitored by Physical Therapist
1	Arterial hypertension; Arthrosis	85	No	Yes	Good	Yes
2	Arterial hypertension; Cardiac arrhythmia; Arteriosclerotic coronary disease; Heart failure	84	Yes	No	Good	Yes
3	Right leg amputation; Umbilical hernia; Arterial hypertension	88	Yes	No	With Slope	No
4	Prostate Cancer; Parkinson's disease; Post-traumatic stress	76	Yes	No	With Slope	No
5	Arterial hypertension; Diabetes mellitus Type II	86	Yes	No	With Slope	No
6	Heart failure; Diabetes mellitus Type II; Arterial hypertension; Depression; Sequelae of surgery to brain injury	83	Yes	No	With Slope	No
7	Heart failure; Diabetes mellitus Type II; Vertigo syndrome; Chronic headaches; Osteoarthritis; Prosthesis in the right humeral; Osteoporosis; Arterial hypertension	81	Yes	No	With Slope	No
8	Osteoarthritis; Depression; Heart failure; Arterial hypertension; Osteoporosis	89	Yes	No	With Slope	No
9	Dementia of vascular etiology; Prostate Cancer; Arterial hypertension; Vertigo syndrome	N/D	No	Yes	Narrow and tight	No
10	Diabetes mellitus Type II; Arterial hypertension; Heart failure; Hyperuricemia; Depression; Bilateral gonarthrosis	N/D	No	Yes	Narrow and tight	No
11	Heart failure; Chronic obstructive pulmonary disease; Bilateral gonarthrosis	97	No	Yes	Narrow and tight	No
12	Diabetes mellitus Type II; Arterial hypertension	71	No	Yes	Narrow and tight	No
13	Arterial hypertension	74	No	Yes	Narrow and tight	No
14	Arterial hypertension; Pulmonary fibrosis; Hyperuricemia; Anemia; Chronic kidney disease; Cardiac arrhythmia; Acute myocardial infarction; Hypocoagulated	N/D	No	Yes	Narrow and tight	No

N/D: The values were not reported.

3. Results

3.1. Data Acquisition

The data were acquired by a mobile application installed in an Android device. It was developed with Android Studio. As presented in Figure 1, the mobile application is composed of components for data acquisition, storage, and send it to a FireBase server. The mobile application acquired data from the onboard sensors, i.e., accelerometer and magnetometer, and two BITalino devices connected by Bluetooth. The BITalino devices receive different sensors' data at a sampling rate of 10 kHz and 16 bits of precision. The data acquired by onboard sensors are collected with a sampling rate of 1 kHz and 16 bits of precision. Firstly, the ECG sensor was attached to the user in three positions with electrodes on the arm. Finally, the EEG sensor was positioned on the head with two electrodes. This position of the sensors was discussed with healthcare professionals related to medicine and physiotherapy subjects.

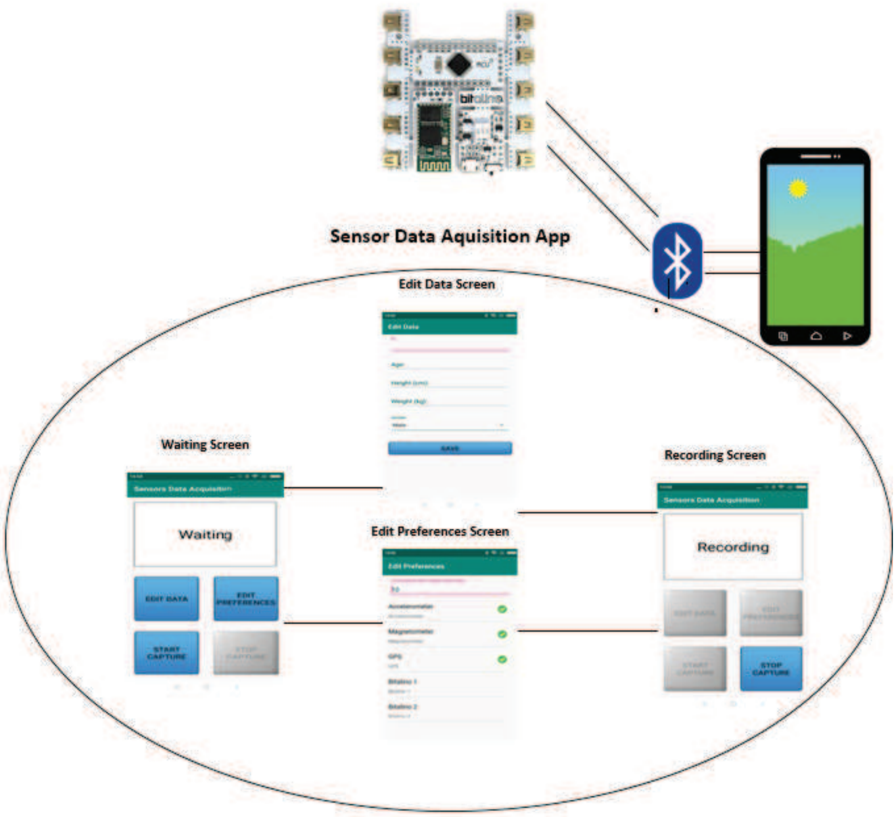

Figure 1. Mobile application.

On the one hand, this mobile application performed a continuous data collection using the built-in magnetometer and accelerometer sensors. The data were collected with a sampling rate of 1 kHz and 16 bits of precision. On the other hand, the mobile application handled the communication technologies required to receive data through Bluetooth from the BITalino device with a pressure sensor. Still, it was also responsible for sending the collected data to the FireBase service for storage.

3.2. Requirements

The requirements for performing the experiments were related to the environment and the individual. The individual must have the mobility to complete the test. For the performance of the Timed-Up and Go test, the material and equipment needed consists of a chair, a tape measure to identify the distance to walk, adhesive tape to mark the end of the three meters, where the individual should reverse the gait, two sports belts, where one is for the mobile device and another one for the BITalino device to measure ECG and EEG data, two BITalino devices and one mobile device. The ECG and EEG sensors consisted of the use of electrodes placed in the individual before the test (i.e., three electrodes for ECG sensor, and two electrodes for EEG sensors).

3.3. Validation

The data acquired from the ECG and EEG sensors allowed us to measure different parameters found in the literature, namely:

- **ECG sensor**: Heart Rate; Linear Heart Rate Variability; Average of QRS interval; Average of R-R interval; Average of R-S interval.
- **EEG sensor**: Frequency; Variability.

In the subsequent sections, the results of the comparison between age and the different variables measured (Section 3.3.1), finalizing this section with the descriptive statistics of the experiments by diseases (Section 3.3.2).

3.3.1. Results by Age

The average age of this group of individuals is 83 years old, varying between a minimum of 71 and a maximum of 97 years of age. The standard deviation is approximately 7 years old, and the respective coefficient of variation (CVs) is 9%, so we can consider the average as a good central indicator of the sample. Thus, in order to study the parameters analyzed by age, we started by organizing individuals into two groups separated by the average sample value, namely individuals aged 83 years or less and individuals aged over 83 years. The age frequency distribution can be seen in Table 3 as ≤83 years old and >83 years old.

Table 3. Frequencies of the different ages.

Class of Age		Frequency	Percent (%)	Valid Percent (%)
Valid	[71; 83]	5	35.7	45.5
	(83; 97]	6	42.9	54.5
	Total	11	78.6	100.0
missing	N/D	3	21.4	
Total		14	100.0	

For the analysis of the signification differences between the averages of age groups, the Student t-test was used to compare the average values. The assumptions of normality were validated, and the equality of variances was tested using the Levene F-test, and it was concluded that the variances between the two age groups for all parameters under analysis are equal (Pr (F > F-test) = p-value > 0.05) (Table 4).

Initially, we processed the ECG and EEG sensor data to identify the different variables. In Table 3, we can also observe the results of the Student's t-test, through the respective limited probability associated with the test statistic (p-value) and the mean values for the different age ranges for the heart rate, linear heart rate variability, the average of QRS interval, the average of R-R interval, and the average of R-S interval variables obtained with the ECG sensor, and the frequency, and variability obtained with the EEG sensor, of the 11 individuals separated by age. Following the results by age, there are no homogeneous groups found in the sample.

Through the results of the t-student test, we can conclude that, statistically, there are no differences between the means of the two age groups for someone of the analyzed parameters ((Pr (|T| > t-test) = p-value > 0.05); that is, age is not discriminating anything within each parameter

Table 4. Average values of the Electroencephalography (EEG) and Electrocardiography (ECG) sensors by age for the 14 studied participants.

Parameters	N	Class Age (Years Old)	Mean ± Standard Deviation	Standard Error of Mean	Minimum	Maximum	*p*-Value	
							F-Test	Student *t*-Test
Heart Rate	5	[71; 83]	90.8 ± 5.6	2.5	86	99	0.295	0.332
	6	(83; 97]	95.5 ± 8.8	3.6	84	107		
Linear Heart Rate Variability (%)	5	[71; 83]	108.2 ± 16	3.8	73	120	0.698	0.898
	6	(83; 97]	104.5 ± 19.5	4.5	58	121		
Average of QRS interval (ms)	5	[71; 83]	654.8 ± 55.5	13.1	578	763	0.347	0.633
	6	(83; 97]	646.6 ± 40.3	9.3	599	714		
Average of R-R interval (ms)	5	[71; 83]	1365.3 ± 371.3	87.5	1018	2013	0.729	0.895
	6	(83; 97]	1543.9 ± 390.9	89.7	899	2169		
Average of R-S interval (ms)	5	[71; 83]	464.6 ± 181.9	42.9	279	683	0.669	0.189
	6	(83; 97]	233.8 ± 139.9	32.1	16	396		
Frequency of EEG	5	[71; 83]	290.5 ± 132.8	31.3	111	434	0.237	0.916
	6	(83; 97]	243.6 ± 58.9	13.5	151	313		
Variability of EEG (%)	5	[71; 83]	88.9 ± 15.8	3.7	64	109	0.239	0.480
	6	(83; 97]	103.6 ± 27.8	6.4	31	122		

3.3.2. Results by Disease

Finally, we processed the ECG and EEG sensor data to identify the different variables. In Table 5, the average values are presented for the heart rate, linear heart rate variability, the average of QRS interval, the average of R-R interval, and the average of R-S interval variables obtained with the ECG sensor, and the frequency, and variability obtained with the EEG sensor of the individuals separated by disease. This analysis was performed with the disorders present in more than one person. Following the results by illness, there are no homogeneous groups found in the sample.

Table 5. Descriptive statistics of the ECG and EEG sensors by disease for the 14 studied participants.

Parameter	Disease	N	Mean ± Standard Deviation	Standard Error of Mean	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Heart Rate	Arterial hypertension	12	93.5 ± 7.2	2.1	89.0	98.1	84	107
	Cardiac arrhythmia	2	86.5 ± 0.7	0.5	80.2	92.9	86	87
	Heart failure	6	90.7 ± 6.0	2.5	84.4	97.0	84	97
	Diabetes mellitus Type II	5	93.2 ± 5.7	2.6	86.1	100.3	86	100
	Depression	3	89.0 ± 7.0	4.0	71.6	106.4	84	97
	Vertigo syndrome	2	94.0 ± 0.0	0.0	94.0	94.0	94	94
	Osteoarthritis	2	89.0 ± 7.1	5.0	25.5	152.5	84	94
	Osteoporosis	2	89.0 ± 7.1	5.0	25.5	152.5	84	94
	Hyperuricemia	2	92.0 ± 7.1	5.0	28.5	155.5	87	97
	Bilateral gonarthrosis	2	97.0 ± 0.0	0.0	97.0	97.0	97	97
	Chronic obstructive pulmonary disease	1	92.0 ± 7.1	5.0	28.5	155.5	87	97
Linear Heart Rate Variability (%)	Arterial hypertension	12	98.4 ± 20.9	6.0	85.1	111.7	58.00	122.00
	Cardiac arrhythmia	2	100.0 ± 22.6	16.0	−103.3	303.3	84.00	116.00
	Heart failure	6	117.4 ± 4.4	1.8	112.7	122.1	110.00	122.00
	Diabetes mellitus Type II	5	104.0 ± 21.8	9.7	77.0	131.0	73.00	122.00
	Depression	3	119.4± 3.4	2.0	111.0	127.8	115.60	122.00
	Vertigo syndrome	2	103.7 ± 23.1	16.4	−104.1	311.4	87.30	120.00
	Osteoarthritis	2	120.4 ± 0.5	0.4	115.9	124.8	120.00	120.70
	Osteoporosis	2	120.4 ± 0.5	0.4	115.9	124.8	120.00	120.70
	Hyperuricemia	2	103.0 ± 26.9	19.0	−138.4	344.4	84.00	122.00
	Bilateral gonarthrosis	2	116.0 ± 8.5	6.0	39.8	192.2	110.00	122.00
	Chronic obstructive pulmonary disease	1	97.0 ± 18.4	13.0	−68.2	262.2	84.00	110.00
Average of QRS interval (ms)	Arterial hypertension	12	634.2 ± 33.0	9.5	613.2	655.1	579.6	686.1
	Cardiac arrhythmia	2	644.1 ± 42.4	30.0	262.9	1025.3	614.1	674.1
	Heart failure	6	647.4 ± 39.6	16.2	605.9	688.9	614.1	713.5
	Diabetes mellitus Type II	5	637.0 ± 29.3	13.1	600.6	673.4	617.3	686.1
	Depression	3	645.9 ± 27.8	16.0	577.0	714.9	620.0	675.2
	Vertigo syndrome	2	637.7 ± 26.5	18.7	400.1	875.3	619.0	656.4
	Osteoarthritis	2	647.1 ± 39.7	28.1	290.1	1004.1	619.0	675.2
	Osteoporosis	2	647.1 ± 39.7	28.1	290.1	1004.1	619.0	675.2
	Hyperuricemia	2	647.1 ± 38.3	27.1	303.4	990.8	620.0	674.1
	Bilateral gonarthrosis	2	666.8 ± 66.1	46.8	72.7	1260.8	620.0	713.5
	Chronic obstructive pulmonary disease	1	693.8 ± 27.9	19.7	443.5	944.1	674.1	713.5
Average of R-R interval (ms)	Arterial hypertension	12	1419.1 ± 285.1	82.3	1238.0	1600.2	899	1725
	Cardiac arrhythmia	2	1507.0± 203.7	144.0	−322.7	3336.7	1363	1651
	Heart failure	6	1433.8 ± 415.2	169.5	998.1	1869.6	1018	2169
	Diabetes mellitus Type II	5	1385.2 ± 282.5	126.3	1034.5	1735.9	1018	1678
	Depression	3	1255.0 ± 52.7	30.4	1124.1	1386.0	1198	1302
	Vertigo syndrome	2	1371.5 ± 499.9	353.5	−3120.1	5863.1	1018	1725
	Osteoarthritis	2	1108.0 ± 127.3	90.0	−35.6	2251.6	1018	1198
	Osteoporosis	2	1108.0 ± 127.3	90.0	−35.6	2251.6	1018	1198
	Hyperuricemia	2	1314.0 ± 69.3	49.0	691.4	1936.6	1265	1363
	Bilateral gonarthrosis	2	1717.0 ± 639.2	452.0	−4026.2	7460.2	1265	2169
	Chronic obstructive pulmonary disease	1	1766.0 ± 569.9	403.0	−3354.6	6886.6	1363	2169

Table 5. *Cont.*

Parameter	Disease	N	Mean ± Standard Deviation	Standard Error of Mean	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Average of R-S interval (ms)	Arterial hypertension	12	336.1 ± 147.3	42.5	242.5	429.6	15.77	683.00
	Cardiac arrhythmia	2	336.0 ± 21.2	15.0	145.4	526.6	321.00	351.00
	Heart failure	6	314.3 ± 214.7	87.6	89.0	539.6	15.77	683.00
	Diabetes mellitus Type II	5	405.4 ± 160.3	71.7	206.4	604.4	277.00	683.00
	Depression	3	208.9 ± 169.7	98.0	−212.6	630.5	15.77	334.00
	Vertigo syndrome	2	515.5 ± 236.9	167.5	−1612.8	2643.8	348.00	683.00
	Osteoarthritis	2	349.4 ± 471.8	333.6	−3889.6	4588.4	15.77	683.00
	Osteoporosis	2	349.4 ± 471.8	333.6	−3889.6	4588.4	15.77	683.00
	Hyperuricemia	2	314.0 ± 52.3	37.0	−156.1	784.1	277.00	351.00
	Bilateral gonarthrosis	2	266.0 ± 15.6	11.0	126.2	405.8	255.00	277.00
	Chronic obstructive pulmonary disease	1	303.0 ± 67.9	48.0	−306.9	912.9	255.00	351.00
Frequency of EEG	Arterial hypertension	12	249.7 ± 88.9	25.7	193.2	306.1	111	434
	Cardiac arrhythmia	2	225.5 ± 24.7	17.5	3.1	447.9	208	243
	Heart failure	6	301.5 ± 67.5	27.6	230.7	372.3	243	434
	Diabetes mellitus Type II	5	283.8 ± 115.5	51.6	140.4	427.2	111	434
	Depression	3	277.7 ± 6.0	3.5	262.7	292.6	272	284
	Vertigo syndrome	2	381.0 ± 75.0	53.0	−292.4	1054.4	328	434
	Osteoarthritis	2	353.0 ± 114.6	81.0	−676.2	1382.2	272	434
	Osteoporosis	2	353.0 ± 114.6	81.0	−676.2	1382.2	272	434
	Hyperuricemia	2	246.0 ± 53.7	38.0	−236.8	728.8	208	284
	Bilateral gonarthrosis	2	291.5 ± 10.6	7.5	196.2	386.8	284	299
	Chronic obstructive pulmonary disease	1	253.5 ± 64.4	45.5	−324.6	831.6	208	299
Variability of EEG (%)	Arterial hypertension	12	90.7 ± 25.6	7.4	74.4	107.0	31.00	122.00
	Cardiac arrhythmia	2	93.5 ± 23.3	16.5	−116.2	303.2	77.00	110.00
	Heart failure	6	108.8 ± 10.8	4.4	97.5	120.2	89.00	122.00
	Diabetes mellitus Type II	5	96.0 ± 13.38	6.0	79.4	112.6	85.00	112.00
	Depression	3	114.3 ± 6.8	3.9	97.4	131.2	109.00	122.00
	Vertigo syndrome	2	84.0 ± 7.1	5.0	20.5	147.5	79.00	89.00
	Osteoarthritis	2	105.5 ± 23.3	16.5	−104.2	315.2	89.00	122.00
	Osteoporosis	2	105.5 ± 23.3	16.5	−104.2	315.2	89.00	122.00
	Hyperuricemia	2	94.5 ± 24.75	17.5	−127.9	316.9	77.00	112.00
	Bilateral gonarthrosis	2	111.5 ± 0.7	0.5	105.2	117.9	111.00	112.00
	Chronic obstructive pulmonary disease	1	94.0 ± 24.0	17.0	−122.0	310.0	77.00	111.00

4. Discussion

4.1. Main Findings

During the performance of the Timed-Up and Go test, we used ECG and EEG sensors to acquire the data and correlate the presence of mental and cardiac diseases. The sample of this study includes a diversity of people with different disorders. Thus, the experimental set was composed of sensors available in the off-the-shelf mobile device, i.e., accelerometer and magnetometer, and a pressure, ECG, and EEG sensors connected to a BITalino device. These sensors are practical to use and non-invasive, allowing the acquisition of different types of data. The data were acquired since the individual gets up from the chair and returns to the initial position.

This test was applied to older adults, who anonymously provided their age and information about their diseases for further analysis of the data acquired. The study of the data was performed considering three viewpoints: the viewpoint by age, by the institution, and by diseases related to cardiac and neurological problems. Between the persons analyzed, none of them reported neurological disorders. They reported illnesses that can be detected with ECG and EEG sensors, including arterial hypertension, arrhythmia, heart failure, coronary artery disease, Parkinson's disease, and others. By the end, the environmental conditions may have also affected the results of the test. The ECG values for the arrhythmia and heart failure are similar, and the values for identifying Parkinson's disease, and bilateral gonarthrosis are identical.

Therefore, we performed two types of analysis. These are the relation of the data acquired by the different sensors and the diseases reported by the individuals. After that, the statistical correlation between the data obtained and the disorders said.

Starting with the analysis of the data reported by the individuals, and based on the information related to the previous works, arterial hypertension may be identified with the amplitude of QRS interval lower than 700 ms, where most of the analyzed individuals reported this disease, except the persons 4 and 11.

In continuation, the identification of persons with arrhythmia or heart rate failure is identified by the irregularities of the heartbeat. Thus, the linear heart rate variability may be used to recognize these types of diseases, verifying if it is higher than 100%. Most of the persons reported these diseases, such as the persons 2, 6, 7, 8, 10, and 11.

Finally, the identification of Parkinson's disease and Bilateral gonarthrosis can be performed with the high average of QRS interval and an average R-R interval of more than 2000 ms, allowing the easy recognition of persons 4 and 11. However, person 10 also has bilateral gonarthrosis, but it is not very well recognized because other diseases are present in this person. In this case, the differences in the data related to the Bilateral gonarthrosis and other diseases are minored.

Due to the different conditions of the test's performance, arterial hypertension is more verified in persons of different ages, except the persons with 76 and 97 years old. Additionally, comparing the different ages, arrhythmia, or heart rate failure is only verified with the increasing, where the persons with age equal to 81, 83, 84, 89, and 97 years old. A pattern of persons with coronary artery disease cannot be identified with the comparison of the different ages. In addition, analyzing the different ages, Parkinson's disease, and Bilateral gonarthrosis can be verified in persons aged 76 and 97.

Generally, the difference is correctly identified with the various parameters and constraints during the data acquisition. There are no diseases related to the EEG reported by the population, but it is verified that the variability of brain activity increases with age. Additionally, brain activity is lower in people with Parkinson's disease.

For the diseases and parameters, the two-way analysis of variance test (two-way ANOVA) was performed with the aim of verifying the interaction between the two factors, in order to understand the presence of a disease affected by the values recorded by ECG and EEG sensors.

The model that includes the sources of disease variation and the interaction parameters vs. diseases is highly significant (Pr (F > F test) = 0 for both sources of variation), which means that there is an interaction between both parameters and disease factors.

Through the analysis of the confidence intervals for the mean of interaction between Heart Rate with Diseases, it is possible to conclude that there are no significant differences between the mean values of this interaction (Figure 2).

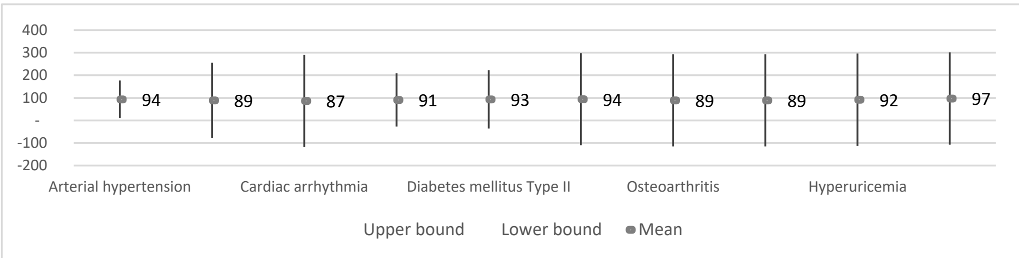

Figure 2. The 95% confidence interval for mean of interaction between Heart Rate with Diseases.

Through the analysis of the confidence intervals for the mean of interaction between Linear Heart Rate Variability with Diseases, it is possible to conclude that there are no significant differences between the mean values of this interaction (Figure 3).

Through the analysis of the confidence intervals for the mean of interaction between Average of QRS interval with Diseases, it is possible to conclude that there are no significant differences between the average values of this interaction (Figure 4).

Through the analysis of the confidence intervals for the mean of interaction between Average of R-R interval with Diseases, it is possible to conclude that there are significant differences between the average values of this interaction. In fact, the average values recorded in patients with Bilateral gonarthrosis is statistically higher than the values recorded in patients with arterial hypertension, depression, Diabetes mellitus Type II, Osteoarthritis and Osteoporosis (Figure 5). On the other hand, in the case of these last two diseases, the averages of QRS interval values are expected to be statistically equal but lower, followed by depression.

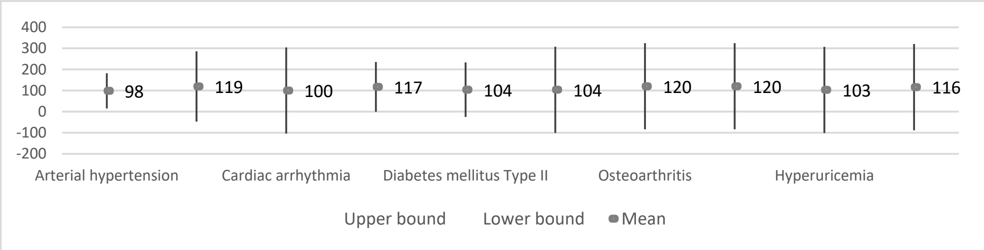

Figure 3. The 95% confidence interval for mean of interaction between Linear Heart Rate Variability with Diseases.

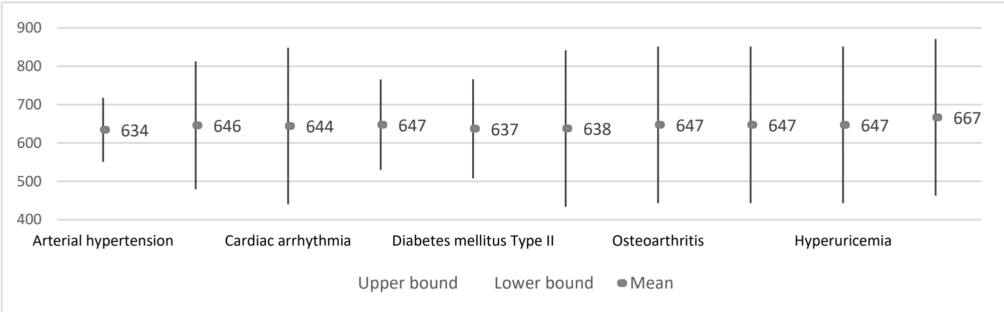

Figure 4. The 95% confidence interval for mean of interaction between Average of QRS interval with Diseases.

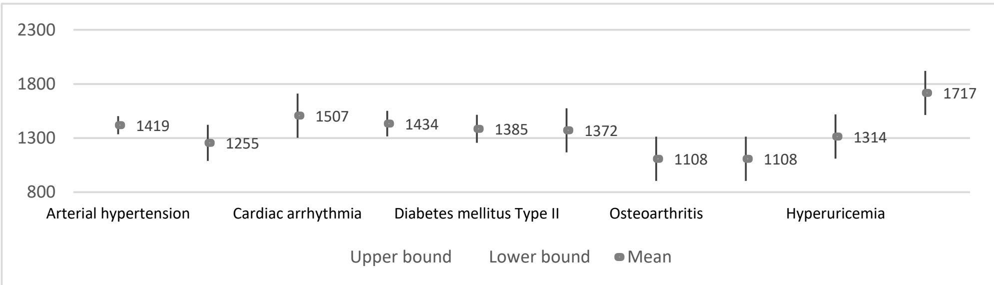

Figure 5. The 95% confidence interval for mean of interaction between Average of R-R interval with Diseases.

Through the analysis of the confidence intervals for the mean of interaction between Average of R-S interval with Diseases, it is possible to conclude that there are no significant differences between the average values of this interaction (Figure 6). Even so, the average value of this parametron in vertigo syndrome is highlighted. On the other hand, we highlight similar intermediate values for arterial hypertension, cardiac arrhythmia, heart failure, osteoarthritis, osteoporosis and hyperuricemia, as opposed to depression with a lower value.

Through the analysis of the confidence intervals for the mean of interaction between Frequency of EEG with Diseases, it is possible to conclude that there are no significant differences between the average values of this interaction (Figure 7). Even so, the average value of this parametron n in vertigo syndrome disease stands out with higher values, followed by osteoarthritis and osteoporosis. In contrast, cardiac arrhythmia, hyperuricemia, and arterial hypertension.

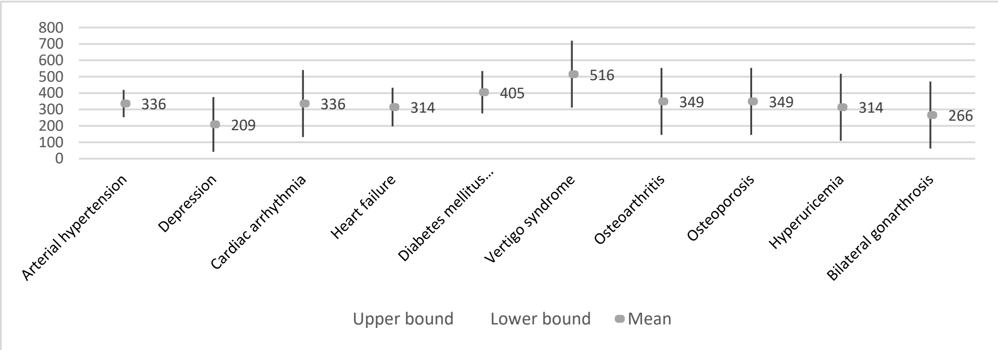

Figure 6. The 95% confidence interval for mean of interaction between Average of R-S interval with Diseases.

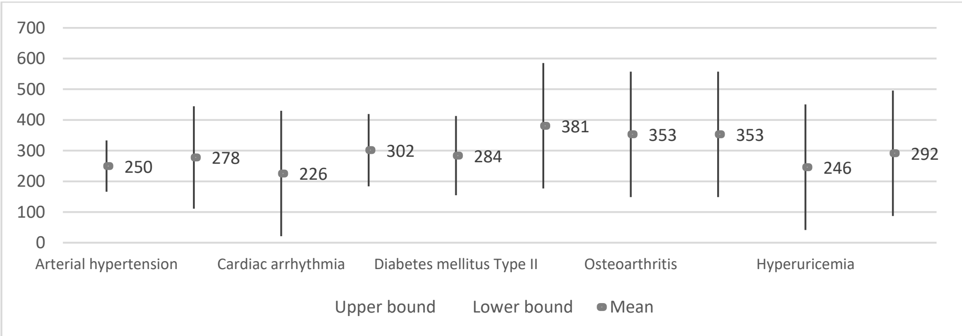

Figure 7. The 95% confidence interval for mean of interaction between Frequency of EEG with Diseases.

Through the analysis of the confidence intervals for the mean of interaction between Variability of EEG with Diseases, it is possible to conclude that there are no significant differences between the mean values of this interaction (Figure 8).

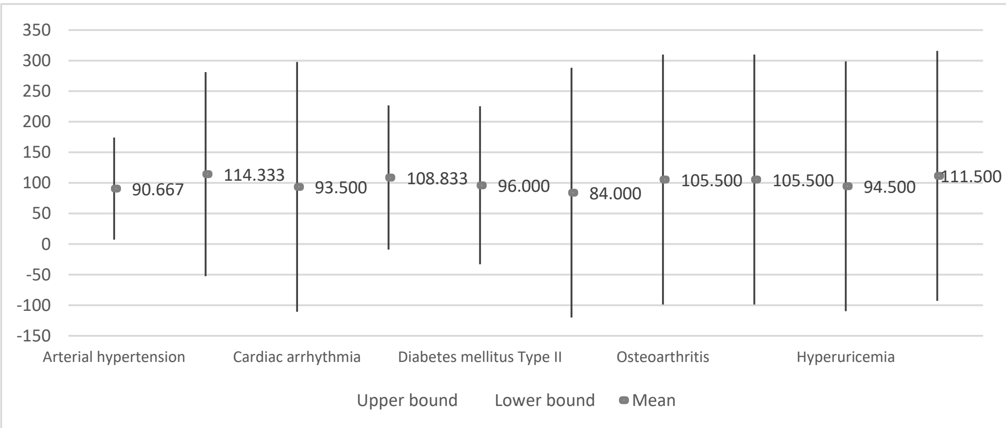

Figure 8. The 95% confidence interval for mean of interaction between Variability of EEG with Diseases.

In Figure 9, we can verify the estimated marginal averages resulting from the interaction between parameters and diseases. The parameters of heart rate, linear heart rate variability, average of QRS amplitude, and EEG variability are practically constant for the diseases analyzed.

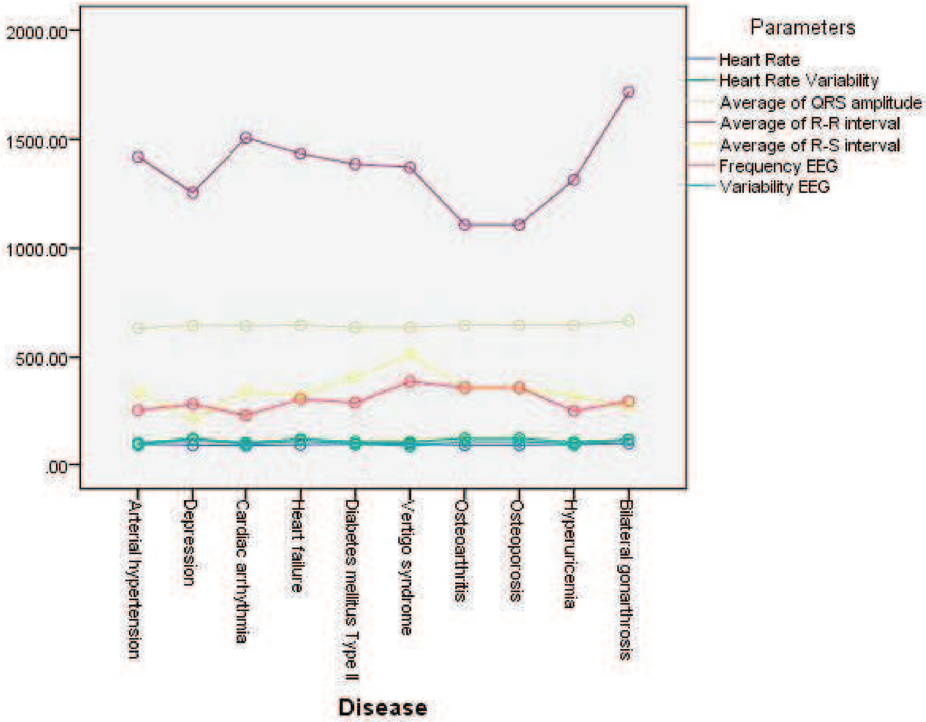

Figure 9. Marginal estimated means of the interaction between diseases and parameters.

In the case of arterial hypertension, cardiac arrhythmia, Diabetes mellitus Type II, Vertigo Syndrome and Hyperuricemia, the values of Average of R-S interval are higher than the values of Frequency EEG. For depression and Bilateral gonarthrosis, the reverse is true.

We can also verify that when these two parameters are the same, we are in the presence of heart failure, osteoarthritis or osteoporosis.

Following the Average of R-R interval, we observed that a large difference between this parameter and the Average of R-S interval can mean the presence of Bilateral gonarthrosis disease, cardiac arrhythmia or arterial hypertension. Lower differences can mean the presence of osteoporosis, osteoarthritis, depression or hyperuricemia.

4.2. Limitations

In carrying out the experiments, the capture and calculation of the different features posed some challenges. Thus, the elderly had very different health states, which meant that the acquired values showed high heterogeneity. The environment for the performance of the test also varies, causing different variations on the data.

As the acquired data were stored in the FireBase service, which needs an available Internet connection that sometimes is not possible in real-time. Additionally, as we were using the BITalino device to acquire the data from pressure, ECG, and EEG sensors, the use of the over-the-air connection, i.e., Bluetooth, failed sometimes, causing some inconsistencies in the data. If detected, the individuals repeated the experiments to obtain reliable data. Commonly, all participants performed the experiments three consecutive times.

Finally, another limitation present in the different experiments was related to data processing and storage, which may be difficult to perform in real-time on the mobile device. The BITalino device does not include the timestamps, but it includes a control bit every 10 ms, where we consider its capture after the start of the data acquisition. The data acquisition was started with an acoustic signal, where the data started to acquire. The major challenge was related to the synchronization of the data acquisition, which was sometimes not possible.

4.3. Comparison with Prior Work

Based on the studies analyzed in Section 1.3, 24 diseases were recognized in the 17 research studies, but the majority lack the presentation of detailed parameters for the detection. Still, the majority (20 diseases) does not present the details about the recognition, providing only information about the use of artificial intelligence. Between the diseases reported in the literature, Cardiovascular death [47] is detected by the measurement of the P-R interval, and the amplitude of QRS complex. Next, the Primary and secondary pulmonary hypertension [48] is detected with the Frontal mid-axis of the QRS complex. Coronary artery disease [51] is detected by the Amplitude of QRS complex, and depressions of S-T and T-wave. A couple of diseases, i.e., Left and right bundle branch block, premature ventricular contraction, Wolff–Parkinson–White syndrome, myocardial ischemia, and myocardial injury are detected by the authors of [53] with durations of P-wave, S-wave, T-wave, QRS interval, P-R interval, Q-T interval, and S-T segment, and the amplitudes of P-wave, R-wave, and T-wave. Parkinson's disease and Bilateral gonarthrosis are detected by the authors of [54] with the duration of R-R interval, P-R interval, QRS interval, and Q-T interval. In [55], left and right ventricular hypertrophies are detected with the measurement of heart rate, amplitudes of P-wave, T-wave, and QRS interval, and durations of P-wave, P-R interval, QRS interval, Q-T interval, and corrected Q-T interval. In continuation, Alzheimer's disease [56,57,62] is commonly detected with statistical, amplitude and frequency-based features, and signal strength, window strength, and sample entropy. Acute ischemic stroke [63] is detected with densities of the power spectrum. Finally, Epilepsy [58–61] is detected with the 2nd order cumulants (mean ± standard deviation), asymmetry, kurtosis, spectral, Renvi, Kolmogorov–Sinai, variance, energy, and the maximum and minimum values of the power spectral density. Between the four diseases that have details about the recognition, i.e., Bradycardia, Tachycardia, Premature ventricular contraction, and Premature atrial contraction, one of them was available in our dataset as presented in Table 6. We also verified the normal values of the different parameters for further comparison [67–69].

Table 6. Values of the different features measured by different studies.

Study	Diseases	Parameters	Values in the Literature	Average Values Obtained in our Study	Normal Values in Healthy Adults
[45]	Bradycardia	Heart rate	<60 bpm	N/A	>60 bpm <92 bpm
[45]	Tachycardia	Heart rate	>100 bpm	N/A	>60 bpm <92 bpm
[45]	Premature ventricular contraction	Duration of QRS interval	>120 ms	N/A	>75.5 ms <108.0 ms
[45]	Premature atrial contraction	Heart rate	>60 bpm <100 bpm	N/A	>60 bpm <92 bpm
[49]	Atrial fibrillation	Duration of P-wave	N/D	N/A	>80 ms <120 ms
		Heart rate	Irregular	N/A	>60 bpm <92 bpm
[50]	Arrhythmia	Heart rate variability	N/D	>100%	N/A
-	Heart rate failure	Heart rate variability	N/A	>100%	N/A
-	Arterial hypertension	Duration of QRS interval	N/A	<700 ms	>75.5 ms <108.0 ms
[54]	Parkinson's disease; Bilateral Gonarthrosis	Duration of R-R interval	N/A	>2000 ms	>600 ms <1200 ms
		Duration of QRS interval	N/A	>700 ms	>75.5 ms <108.0 ms

N/A: Not Available. N/D: Not Defined.

However, the diseases highlighted in Table 6 were present in our dataset, which verified different conditions for its recognition.

Considering the values available in Table 6, it is possible to verify the effects of different diseases and the age of people analyzed in the different studies. The values presented by the authors of [45] are correlated between older adults and healthy adults. The values presented by the authors of [49] are not comparable as the authors did not present the values obtained. The authors of [50] also did not present the values of heart rate variability, but a pattern was verified with our study. Comparing the values reported in other studies to the ones reported in our study, it is evident that the durations of R-R and QRS intervals are higher in older adults. This is an interesting observation that could have policy implications. For example, some policies might be enhanced to include additional analysis with ECG and EEG during Timed Up and Go tests to hopefully detect some emerging medical conditions before they become too serious. However, in some cases, our dataset may not be enough for the identification of the right patterns, as verified in the recognition of Coronary artery disease. To do that, more individuals with different disorders are needed. Likewise, if some medical condition is identified with the proposed approach, it should be validated with a more traditional clinical method to avoid false positives.

5. Conclusions

The use of functional tests with systems that allow the acquisition of biological signals presents an optimal combination when we want to conclude investigations of this type, and the main goals of this study were to design and develop a method for the acquisition, analysis, and identification of different patterns of diseases with low-cost sensors.

As it was included in research on the results of the Timed-Up and Go test, it was only possible to collect the ECG and EEG signals from a small number of individuals. In the future, this study should be extended to a larger sample to investigate other dependencies. The reported values are in line with other studies in the literature.

In this sense, the Timed-Up and Go test, with all its phases and aspects, presents itself as a great example because it allows the analysis of data related to movement and therefore applied to physiotherapy. On the other hand, the measurement of physical effort and the measurement of signals related to the cardiac and neurological systems can also be calculated and analyzed.

The ECG and EEG data allow us to know and analyze the functioning of the heart and brain during the effort. The use of statistical methods of analysis based on the variance in each individual, considering their physical state, allows us to know and build a set of relationships and patterns for each of the diseases related to the cardiac and neurological system.

The presented results show that it is possible to find correlations between existing diseases and different features extracted from ECG and EEG signals collected during Timed-Up and Go tests. The applied statistical methods suggest that investigation of this type can be critical in helping doctors and in the first analysis of a patient. It shows patterns in the analyzed diseases, showing that people with the same diseases have very similar values, which is very encouraging considering the aim of the study—to detect emerging medical conditions early on. The main contribution of this paper is that the proposed solution was developed end-to-end and uses affordable sensors and devices, and computational methods that are easily deployed on mobile devices with limited computing power and battery capacity.

In the future, and as the development of this research, it will be important to apply artificial intelligence and machine learning methods to allow the calculation and identification of diseases automatically.

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4.3. Machine Learning Techniques with ECG and EEG Data: An Exploratory Study

The following article is the second part of the chapter 4.

Machine Learning Techniques with ECG and EEG Data: An Exploratory Study

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Machine Learning Techniques with ECG and EEG Data: An Exploratory Study

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Abstract: Electrocardiography (ECG) and electroencephalography (EEG) are powerful tools in medicine for the analysis of various diseases. The emergence of affordable ECG and EEG sensors and ubiquitous mobile devices provides an opportunity to make such analysis accessible to everyone. In this paper, we propose the implementation of a neural network-based method for the automatic identification of the relationship between the previously known conditions of older adults and the different features calculated from the various signals. The data were collected using a smartphone and low-cost ECG and EEG sensors during the performance of the timed-up and go test. Different patterns related to the features extracted, such as heart rate, heart rate variability, average QRS amplitude, average R-R interval, and average R-S interval from ECG data, and the frequency and variability from the EEG data were identified. A combination of these parameters allowed us to identify the presence of certain diseases accurately. The analysis revealed that the different institutions and ages were mainly identified. Still, the various diseases and groups of diseases were difficult to recognize, because the frequency of the different diseases was rare in the considered population. Therefore, the test should be performed with more people to achieve better results.

Keywords: Artificial intelligence; electrocardiography; electroencephalography; feature extraction; recognition of diseases

1. Introduction

The emergence of non-invasive methods for analyzing and detecting diseases is one of the most significant prospects in medicine. At the same time, this poses challenges related to the correct use of technology, the positioning of the sensors, and the constant evolution of the equipment [1,2]. Technological advancements allow for a preliminary diagnosis through machines without any intervention from healthcare professionals. This research is included in the development of systems to support ambient assisted living technologies [3–6]. Cutting-edge approaches in the healthcare area have helped in solving various computer vision-based tasks by analyzing different features from various biosignals, including the facial features [7,8].

Mobile devices can be connected to different devices to head the creation of sophisticated hand-held systems for the monitoring of health states [9–11]. They are handy because they are portable and small, allowing their correct positioning for different measurements [9–11]. These devices are equipped with different sensors, but more sensors can be connected through over-the-air connections [12–18]. These devices with increasing number of functionalities, and the number of available sensors, boost the options for creation of systems that could assist older adults [15,19–22]. The use of this data captured in each individual and their subsequent calculation present the potential of these projects.

This research is included in a project related to Timed-Up and Go test, where the individuals were provided with a smartphone having an accelerometer and magnetometer sensors. To perform the experiments, we used two BITalino devices (https://bitalino.com/en/) that are affordable do-it-your-self boards facilitating the collection and analysis of variety of biomedical signals with inexpensive sensors. First, a BITalino device was positioned on the chair with a force sensor to detect the duration for which the individuals stood. Then, another BITalino device, with ECG and EEG sensors, was placed in the individual, and the different sensors were prepared for the acquisition of data during the test. Regarding the data acquired by the mobile device, the sampling rate is around 10 ms. Then, for the data acquired by the BITalino device, the sampling rate is exactly 100 ms. The similar frequencies enable the comparison of the data more accurately.

The main purpose of this study was the implementation of neural networks to identify the different diseases present in the population considered in the study reported in [23,24]. It was related to the timed-up and go test's execution with institutionalized people from the Covilhã and Fundão municipalities. Thus, the implementation of the methods started with identifying persons by institutions, age, diseases, and groups of diseases.

The implemented neural networks with the WEKA software [25] reported that the individuals might be recognized by institutions, where only the individuals from Centro Comunitário das Lameiras were not correctly identified. Similar results were obtained by age, where only persons who were 74, 85, and 86 years old were not correctly recognized. Regarding the recognition of the diseases, they were not correctly identified, because the sample consisted of a small number of individuals. However, after the categorization of the illnesses, cardiac diseases started to be recognized as a group of diseases.

Other studies related to processing of ECG and EEG data are reviewed and summarized in [26,27]. There are two main tracks regarding feature extraction—based on statistical features from the time and frequency domain, and ones based on deep learning. Our approach is using classical feature extraction because of the limited dataset size that we have. The results are on par with other approaches with a similar number of participants. What is novel in our approach is the combination of both sensors embedded on an inexpensive board, proving that even such affordable devices can provide satisfactory results and serve as indication of emerging diseases.

The Introductory section ends with this paragraph, and the remaining sections of this paper are organized as follows: Section 2 presents the description of the structure of the method implemented for the recognition of persons by institution, age, diseases, and groups of diseases. The results obtained are presented in Section 3. This paper ends with the discussion of the results and the presentation of the different conclusions in Section 4.

2. Methods

Machine learning methods were implemented with ECG and EEG data to identify the persons by the institution, age, diseases, and groups of disorders. The flow of the proposed method includes several stages, including data collection, feature extraction, machine learning, and statistical methods, as presented in Figure 1. We only considered the persons whose ECG and EEG data were correctly acquired, and the data were not filtered, extracting only the different features.

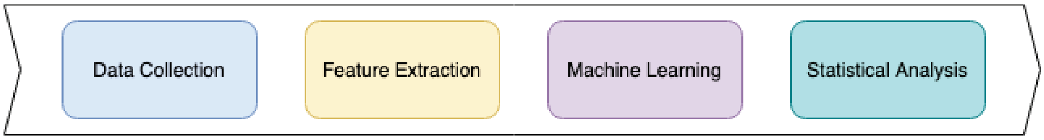

Figure 1. Flow of the analysis of the collected data.

2.1. Data Collection

Following the previous studies [23,24], the data, as presented in Table 1, were acquired from 14 institutionalized individuals aged between 71 and 97 years old (83 +/− 7.4) with different diseases included in some categories, as presented in Section 3.4. The different data were acquired from various institutions, such as Centro Comunitário das Lameiras, Lar Minas, Lar da Misericórdia, and Lar da Nossa Senhora de Fátima. The data were collected by a mobile application connected by Bluetooth to a BITalino device. Different constraints were verified during the data collection, but these records were reliable for the analysis and correlation of the different diseases found in the population. For this study, only the ECG and EEG data acquired by a BITalino device were considered for the processing of the different disorders. The data acquisition faced some challenges, as presented in [28,29].

The acquisition of the data has different sample rate between devices, where the sampling rate of the sensors available in the mobile device is variable, because the instruction Sensor.DELAY_FASTEST does not have the same frequency on all devices. Regarding the device used, i.e., XIAOMI MI 6, reported that the frequency is around 10 ms, i.e., 100 Hz. Next, the sampling rate of the BITalino device connected by Bluetooth is 100 Hz. After the data acquisition, the different features were extracted for further comparison, as explained in Section 2.2. After the data acquisition, the data were processed offline as presented in Section 2.3.

Table 1. Different characteristics of the population analysed.

Person ID	Institution	Age	Disease	Disease Category
1	Centro Comunitário das Lameiras	85	Arterial hypertension	Cardiovascular
			Arthrosis	Osteoarticular
2	Lar Minas	84	Arterial hypertension; Cardiac arrhythmia; Arteriosclerotic coronary disease; Heart failure	Cardiovascular
3		88	Right leg amputation	Osteoarticular
			Umbilical hernia	Digestive system and abdominal wall
			Arterial hypertension	Cardiovascular
4		76	Prostate Cancer	Nephro-urological
			Parkinson's disease	Neurological and balance
			Post-traumatic stress	Psychiatric
5	Lar da Misericórdia	86	Arterial hypertension	Cardiovascular
			Diabetes mellitus Type II	Metabolic
6		83	Heart failure; Arterial hypertension	Cardiovascular
			Diabetes mellitus Type II	Metabolic
			Depression	Psychiatric
			Sequelae of surgery to brain injury	Neurological and balance
7		81	Heart failure; Arterial hypertension	Cardiovascular
			Diabetes mellitus Type II	Metabolic

			Osteoarthritis; Prosthesis in the right humeral; Osteoporosis	Osteoarticular
8		89	Osteoarthritis; Osteoporosis	Osteoarticular
			Depression	Psychiatric
			Heart failure; Arterial hypertension	Cardiovascular
9		N/D	Dementia of vascular etiology; Arterial hypertension	Cardiovascular
			Prostate Cancer	Nephro-urological
10		N/D	Diabetes mellitus Type II; Hyperuricemia	Metabolic
			Arterial hypertension; Heart failure	Cardiovascular
			Depression	Psychiatric
			Bilateral gonarthrosis	Osteoarticular
11	Lar da Nossa Senhora de Fátima	97	Heart failure	Cardiovascular
			Chronic obstructive pulmonary disease	Lung
			Bilateral gonarthrosis	Osteoarticular
12		71	Diabetes mellitus Type II	Metabolic
			Arterial hypertension	Cardiovascular
13		74	Arterial hypertension	Cardiovascular
14		N/D	Arterial hypertension; Cardiac arrhythmia; Acute myocardial infarction	Cardiovascular
			Pulmonary fibrosis	Lung
			Hyperuricemia	Metabolic
			Chronic kidney disease	Nephro-urological

2.2. Feature Extraction

Different features were extracted with the framework [4] from the ECG and EEG signals, including heart rate, heart rate variability, average QRS amplitude, average R-R interval, and the average R-S interval from the ECG data, and the frequency and variability from the EEG data. These data were combined for the identification of institution, age, disease, and a group of disorders of different individuals.

2.3. Machine Learning

The machine learning method implemented was a neural network, i.e., multiplayer perceptron, implemented with the WEKA software [25] with the following details:

- Learning rate: 0.3;
- Momentum: 0.2;
- Normalization of attributes and classes;
- Seed value: 0;
- Training time: 500ms;
- Validation Threshold: 20.

The WEKA software is a free and open-source application to test different machine learning methods. It includes a set of methods, but we chose the Multiplayer Perceptron method [30,31], which is a method that consists of the training and the prediction of different classes with different weights to the input and output neurons. It also supports different attribute transformation methods, including ones for handling nominal and numeric data, which is important for medical datasets, which frequently encounter mixed data types [32,33].

2.4. Statistical Analysis

For the validation of the implemented method, different parameters were calculated, such as true positive (TP), false positive (FP), true negative (TN), and false negative (FN). With these values, the accuracy, precision, recall, and F1 score values were calculated to measure the performance of the implemented method.

3. Results

Based on the different constraints during data acquisition, we performed various types of analyses with neural networks, firstly, by combining the institution with the different features extracted (Section 3.1). Secondly, we combined the different features extracted with the sample's different ages (Section 3.2). Thirdly, we combined the same features extracted with various diseases (Section 3.3). Finally, we established groups of disorders, and the disorders were categorized; then, we combined the different groups of illnesses with the features extracted previously (Section 3.4).

3.1. Analysis by Institution

Based on the implementation of the machine learning methods described in Section 2.3 with the data separated by institution, Table 2 presents the confusion matrix of the results obtained. We verified that the records from Centro Comunitário das Lameiras were not correctly identified, but the persons from the remaining institutions were correctly identified. The data were selected with WEKA software as shown in Figure 2, presenting the classification dispersed by the different institutions (Figure 3), such as Centro Comunitário das Lameiras, Lar Minas, Lar da Misericórdia, and Lar da Nossa Senhora de Fátima.

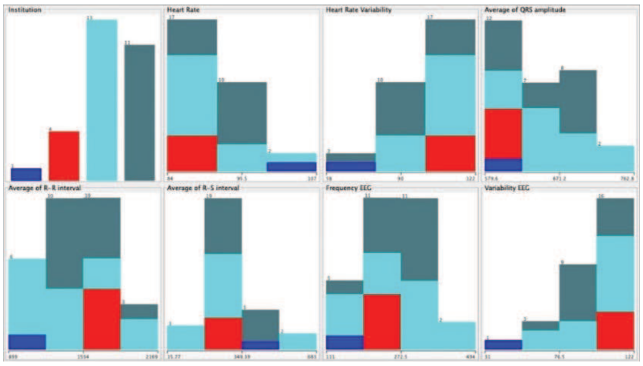

Figure 2. Descriptive analysis of the data by Institution.

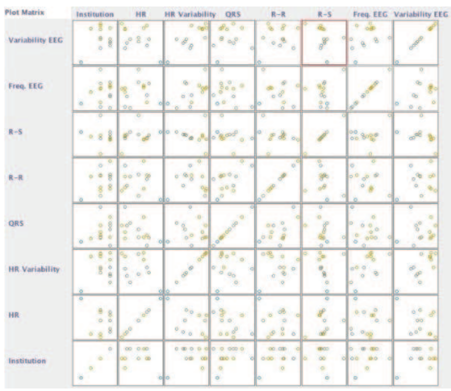

Figure 3. Plot dispersion of the classified data by Institution.

Table 2. Confusion Matrix for the analysis by Institution.

		Predicted Class			
		Centro Comunitário das Lameiras	**Lar Minas**	**Lar da Misericórdia**	**Lar da Nossa Senhora de Fátima**
Actual Class	Centro Comunitário das Lameiras	0	0	1	1
	Lar Minas	0	4	0	0
	Lar da Misericórdia	0	0	24	1
	Lar da Nossa Senhora de Fátima	0	0	1	23

Next, the results of the identification of the persons from the institutions performed with neural networks, as presented in Table 3, showed that the persons from Lar Minas were correctly discretized, where the persons from Centro Comunitário das Lameiras were not identified. The remaining institutions were commonly identified, reporting one record that was not correctly identified in each institution. Thus, the use of neural networks resulted in an accuracy of 93% with a precision of 89%. Moreover, the recall value was 93%, and the F1 Score was 91%.

Table 3. Results of the analysis by Institution.

Institution	Accuracy	Precision	Recall	F1 Score
Centro Comunitário das Lameiras	0%	0%	0%	0%
Lar Minas	100%	100%	100%	100%
Lar da Misericórdia	96%	92%	96%	94%
Lar da Nossa Senhora de Fátima	96%	92%	96%	94%
Total	93%	89%	93%	91%

3.2. Analysis by Age

As the different institutions had different types of people, we implemented the machine learning methods with the data separated by age. Table 4 presents the confusion matrix of the results obtained. We verified that the records related to persons aged 74, 85, and 86 years old were not correctly identified. The data were selected with WEKA software as presented in Figure 4, showing the classification dispersed by the different ages in the following order (Figure 5): 85, 84, 88, 76, 86, 83, 81, 89, N/D, 97, 71, and 74.

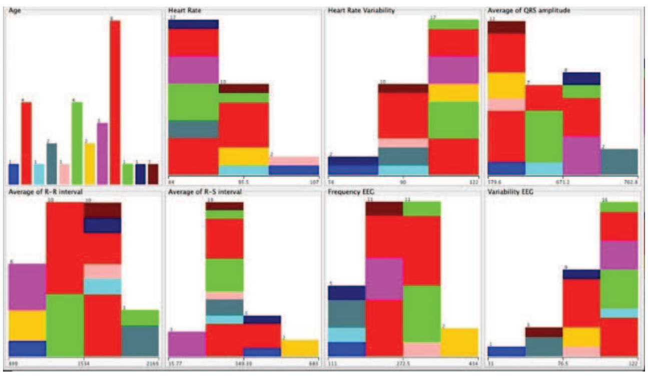

Figure 4. Descriptive analysis of the data by age.

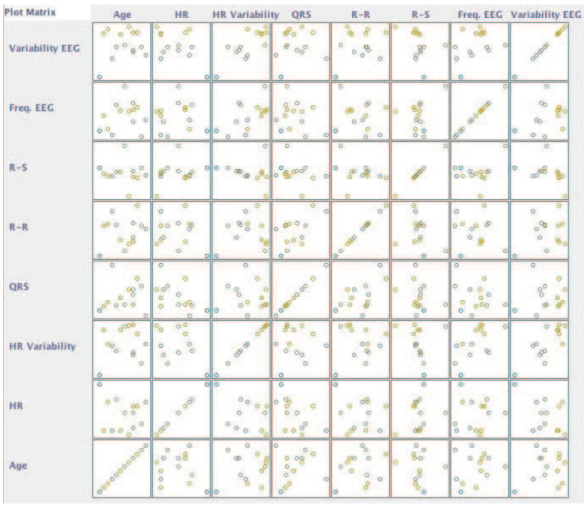

Figure 5. Plot dispersion of the classified data by age.

Table 4. Confusion Matrix for the analysis by age.

		Predicted Class											
		71	**74**	**76**	**81**	**83**	**84**	**85**	**86**	**88**	**89**	**97**	**N/D**
Actual Class	71	2	0	0	0	0	0	0	0	0	0	0	0
	74	0	0	0	0	0	0	0	1	0	0	0	0
	76	0	0	3	0	0	0	0	0	0	0	0	0
	81	0	0	0	7	0	0	0	0	0	0	0	0
	83	0	0	0	0	5	0	0	0	0	0	0	0
	84	0	0	0	0	0	4	0	0	0	0	0	0
	85	0	0	0	0	0	0	1	1	0	0	0	0
	86	0	1	0	0	0	0	0	1	0	0	0	0
	88	0	0	0	0	0	0	0	0	3	0	0	0
	89	0	0	0	0	0	0	0	0	0	5	0	0
	97	0	0	0	0	0	0	0	0	0	0	3	0
	N/D	0	0	0	0	0	0	0	0	0	0	0	18

Next, the results of the identification of the persons by age performed with neural networks, as presented in Table 5, showed that the 74 years-old people were not correctly identified at all. Concerning the 85 and 86 years-old, only 50% of the cases were correctly identified. Finally, the method reported an accuracy of 95%, precision of 96%, recall value of 95%, and F1 score of 95%.

Table 5. Results of the analysis by age.

Age	Accuracy	Precision	Recall	F1 Score
71	100%	100%	100%	100%
74	0%	0%	0%	0%
76	100%	100%	100%	100%
81	100%	100%	100%	100%
83	100%	100%	100%	100%
84	100%	100%	100%	100%
85	50%	100%	50%	67%
86	50%	33%	50%	40%
88	100%	100%	100%	100%
89	100%	100%	100%	100%

97	100%	100%	100%	100%
N/D	100%	100%	100%	100%
Total	95%	96%	95%	95%

3.3. Analysis by Diseases

The subjects of this study had different diseases, and we verified, with the implementation of neural networks, which disorders did not correlate with the different acquired data. We confirmed that this was because we had a limited number of persons with each disease. However, the negative cases were correctly identified, reporting an accuracy between 89% and 98%, as shown in Table 6. The data were selected with WEKA software as presented in Figure 6, showing the classification dispersed by the different diseases in the following order (Figure 7): arterial hypertension, cardiac arrhythmia, arteriosclerotic coronary disease, heart failure, Parkinson's disease, post-traumatic stress, depression, sequelae of surgery to brain injury, dementia of vascular etiology, and acute myocardial infarction.

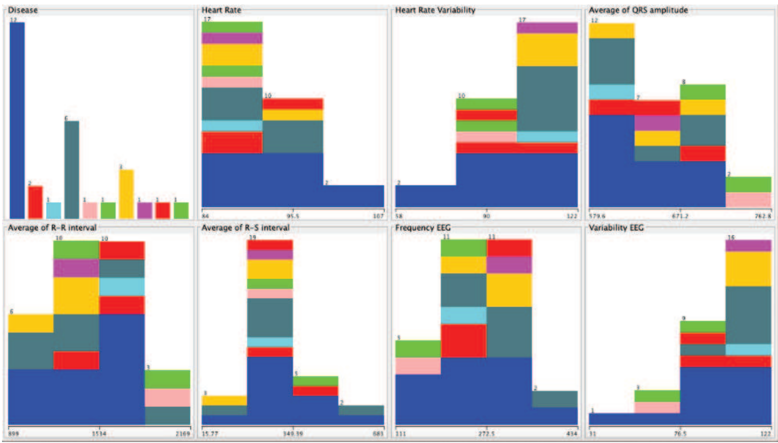

Figure 6. Descriptive analysis of the data related by disease.

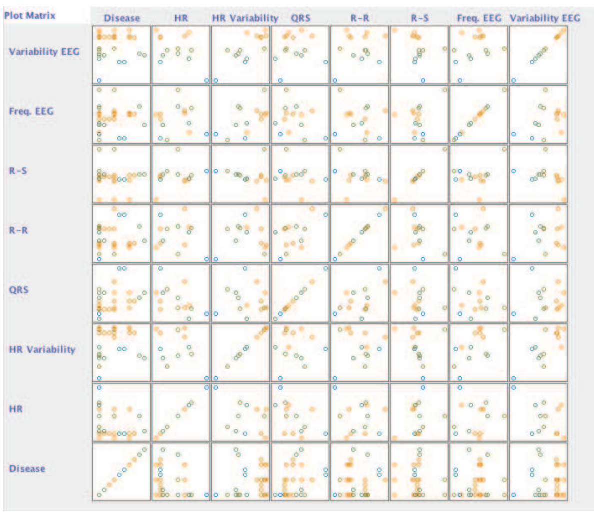

Figure 7. Plot dispersion of the classified data by disease.

Table 6. Results of the analysis by each disease.

	True Positive	False Positive	False Negative	True Negative	Accuracy	Precision	Recall	F1 Score
Arterial Hypertension	1	11	5	38	71%	74%	64%	70%
Arthrosis	0	1	1	53	96%	98%	96%	96%
Cardiac arrhythmia	0	2	0	53	96%	93%	96%	94%
Arteriosclerotic coronary disease	0	1	0	54	98%	96%	98%	97%
Heart Failure	0	6	0	49	89%	79%	89%	84%
Right leg amputation	0	1	0	54	98%	96%	98%	97%
Umbilical hernia	0	1	0	54	98%	96%	98%	97%
Prostate Cancer	0	2	1	52	95%	93%	95%	94%
Parkinson's disease	0	1	1	53	96%	96%	96%	96%
Post-traumatic stress	0	1	1	53	96%	96%	96%	96%
Diabetes mellitus Type II	0	5	0	50	91%	83%	91%	87%
Depression	0	3	0	52	95%	89%	95%	92%
Sequelae of surgery to brain injury	0	1	0	54	98%	96%	98%	97%
Osteoarthritis	0	2	0	53	96%	93%	96%	95%
Prosthesis in the right humeral	0	1	0	54	98%	96%	98%	97%
Osteoporosis	0	2	0	53	96%	93%	96%	95%
Dementia of vascular etiology	0	1	0	54	98%	96%	98%	97%
Hyperuricemia	0	2	0	53	96%	93%	96%	95%
Bilateral gonarthrosis	0	2	1	52	95%	93%	95%	94%
Pulmonary fibrosis	0	1	0	54	98%	96%	98%	97%
Chronic obstructive pulmonary disease	0	1	0	54	98%	96%	98%	97%
Chronic kidney disease	0	1	0	54	98%	96%	98%	97%
Acute myocardial infarction	0	1	0	54	98%	96%	98%	97%

3.4. Analysis by Group of Diseases

As previously verified, there was no correlation between the values acquired from the ECG and EEG sensors and the different diseases. Therefore, we grouped the different disorders by categories, such as osteoarticular diseases, cardiovascular diseases, lung diseases, neurological and balance diseases, psychiatric illnesses, nephro-urological diseases, digestive system and abdominal wall diseases, and metabolic disorders, as presented in Table 7.

Table 7. Classification of different diseases.

Classification Category	Diseases
Osteoarticular	Arthrosis; Right leg amputation; Bilateral gonarthrosis; Osteoarthritis; Prosthesis in the right humeral; Osteoporosis
Cardiovascular	Arterial Hypertension; Cardiac arrhythmia; Arteriosclerotic coronary disease; Heart failure; Acute myocardial infarction
Lung	Pulmonary fibrosis; Chronic obstructive pulmonary disease
Neurological and balance	Parkinson's disease; Dementia of vascular etiology; Sequelae of surgery to brain injury
Psychiatric	Post-traumatic stress; Depression; Chronic kidney disease; Prostate cancer
Digestive system and abdominal wall	Umbilical hernia
Metabolic	Hyperuricemia; Diabetes mellitus Type II

After the grouping of different diseases, the neural networks were applied to the various records grouped by diseases. As shown in Table 8, the results improved. The identification of persons with cardiovascular diseases had an accuracy of 51%. As in the case of the detection of isolated diseases, the negative cases were correctly identified, reporting an accuracy between 51% and 98%.

Table 8. Results of the analysis by groups of diseases.

	True Positive	False Positive	False Negative	True Negative	Accuracy	Precision	Recall	F1 Score
Cardiovascular	6	17	10	22	51%	56%	49%	51%
Osteoarticular	0	9	3	43	78%	69%	78%	73%
Digestive system and abdominal wall	0	1	0	54	98%	96%	98%	97%
Nephro-urological	0	5	2	48	87%	82%	87%	85%
Neurological and balance	0	2	2	51	93%	93%	93%	93%
Psychiatric	0	4	0	51	93%	86%	93%	89%
Metabolic	0	9	1	45	82%	70%	82%	75%
Lung	0	2	0	53	96%	93%	96%	95%

As we are only acquiring data related to ECG and EEG sensors, the reported results are the expected. Thus, we analysed the groups of diseases that are related to this type of data, such as Cardiovascular diseases, Neurological and balance diseases, and Psychiatric illnesses, resulting in Table 9. It is also verified that the most recognized conditions are the Cardiovascular diseases with an accuracy of 76%. The data was selected with WEKA software as presented in Figure 8, presenting the classification dispersed by the different diseases in the following order (Figure 9): cardiovascular, neurological and balance, and psychiatric.

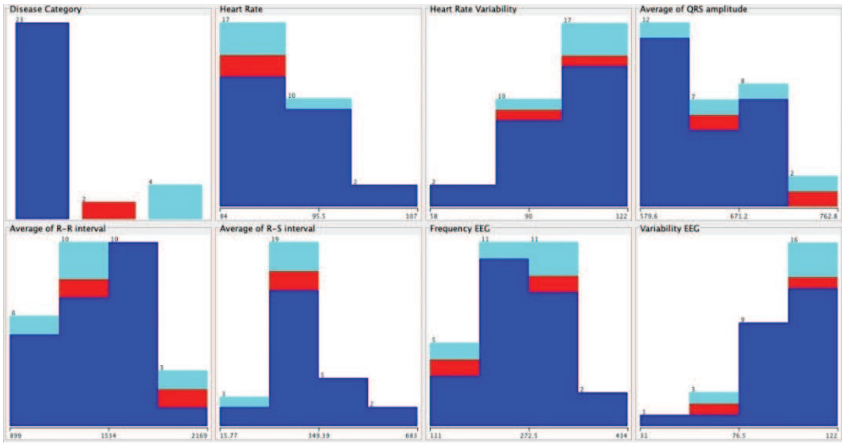

Figure 8. Descriptive analysis of the data related by groups of diseases.

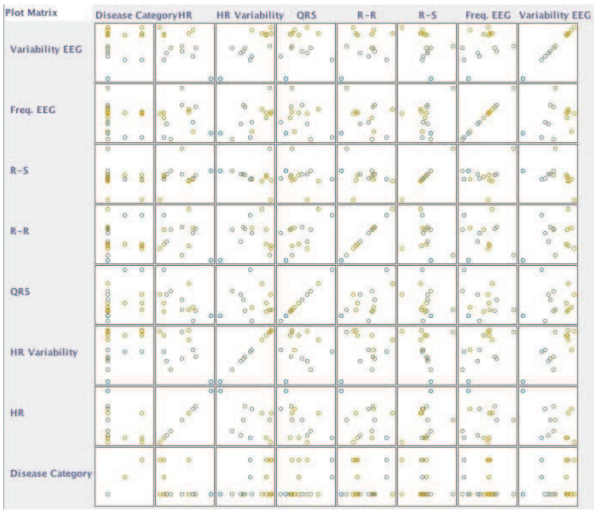

Figure 9. Plot dispersion of the classified data by groups of diseases.

Table 9. Confusion Matrix and results of the analysis by groups of diseases related to ECG and EEG data.

	True Positive	False Positive	False Negative	True Negative	Accuracy	Precision	Recall	F1 Score
Cardiovascular	20	3	4	2	76%	74%	76%	75%
Neurological and balance	0	2	2	25	86%	86%	86%	86%
Psychiatric	0	4	2	23	74%	73%	79%	76%

4. Discussion and Conclusions

Machine learning techniques are helpful for the recognition of different diseases involved in the studied population. The application of machine learning techniques made it possible to identify with some accuracy the different patterns related to the extracted features, such as heart rate, heart rate variability, average QRS amplitude, average R-R interval, and average R-S interval from ECG data, and the frequency and variability from the EEG data. A combination of these parameters allowed us to identify, with some accuracy, the presence of certain diseases.

However, this study revealed some limitations related to the data acquisition and different constraints, and some data were excluded for several reasons, including the failure of the sensors. A small number of valid records implies that the machine learning method might benefit from larger datasets and samples for them to be reliable.

The obtained results revealed that the individuals related to institutions were recognized except for individuals from Centro Comunitário das Lameiras. The identification results related to age were also accurate except for the results for persons aged 74, 85, and 86 years old. Regarding the recognition of diseases and considering that we had a small dataset for the analysis, the isolated disorders were not recognized. However, when the disorders were categorized, some persons with cardiovascular diseases were identified. Thus, the proposed method reported low accuracies for illnesses, but the accuracy was higher for the recognition of persons by age and institution.

In the future we intend to study a larger number of individuals to increase the size of the dataset acquired. Next, other types of diseases will be analyzed, comparing healthy people with those suffering from certain disorders.

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5. Conclusion

The focus of this master's dissertation is related to the instrumentation of the Timed-Up and Go test for the field of physical therapy. It was performed with the use of sensors available in off-the-shelf mobile devices, *e.g.*, accelerometer, magnetometer and gyroscope, and the pressure, Electrocardiography and Electroencephalography sensors connected to the BITalino devices. The different characteristics of the signals from the various sensors were analyzed to extrapolate the different conclusions related to the performance of the test. The use of such devices can be an excellent complement to the devices currently used because they are incredibly reliable and available at a low price as compared to specific devices.

Mobile devices embed several sensors, including accelerometer, magnetometer, gyroscope, and Global positioning System (GPS) receiver. These sensors allow the acquisition of different types of physical and physiological parameters. The sensors connected to the BITalino devices were connected over Bluetooth, presenting themselves as an excellent complement to the sensors embedded in the mobile devices, because due to the ease of programming, they allowed an increase in the number of functionalities that the mobile devices already had.

The main objective of this work described in this dissertation was the creation of a method that allowed the instrumentation of the Timed-Up and Go test by using sensors. It also enabled the acquisition of different sensors' signals for the automatic calculation of features related to the movement, comparing the results with diseases that the individuals who participated in the study had thus allowing the creation of standards for each disorder.

Thus, during this dissertation, several signals were acquired using various sensors during the performance of the Timed-Up and Go test, by applying statistical analysis and artificial intelligence methods to identify the different phases of the test and validate its execution.

This dissertation was carried out in different phases, in which, initially, the study on the state-of-the-art technology for the instrumentalization of the Timed-Up and Go test was carried out. This analysis consisted of the analysis of the characteristics, methods and sensors previously used in the literature. Moreover, several studies on the detection of diseases related to movement were analyzed.

Then, the architecture of the proposed system with different sensors and devices was developed, defining the Timed-Up and Go test and the positioning of the sensors during the same.

Then, the system was implemented, and several tests were performed, proceeding to the calculation of the signal characteristics of the different sensors and analyzing the different limitations previously presented. This dissertation includes the presentation of the results, the study design, the difficulties encountered during the data acquisition in various environments and a statistical analysis with the performance of the results of the multiple features, with various perspectives per person, per institution and by disease for the pressure sensors, accelerometers, and magnetometers. It proves the effectiveness of the method and how mobile devices can be quite useful in such investigations, as well as the varied conclusions drawn from the multiplicity and heterogeneity of the data present, as we used older adults for the experiments and therefore with varying degrees and physical states. Next, this dissertation presented the calculation, study design, difficulties in data acquisition, methods of data acquisition, processing and results for the experiments carried out and the use of the data acquired from the Electroencephalography and Electrocardiography sensors. It concluded that it was possible to obtain data related to cardiac and cerebral activities, to compare them from different perspectives such as by individuals, their diseases and the space where these data were acquired. The obtained results were used to calculate the duration of each QRS complex, which it was verified that is was correlated with the different health diseases present in the population. It ends with the validation of the acquired data for diseases related to the heart and brain by using Artificial Neural Networks algorithms. It was possible to conclude that machine learning algorithms could be used for calculating and identifying diseases and to determine the reliability of the datasets that were used. Thus, an accuracy of between 89% and 96% implied a very high percentage of reliability and efficiency in the recognition of the different variables, which allowed us to conclude that this type of data and the method were very reliable.

Thus, with the accelerometer, magnetometer and pressure sensor, the following characteristics were identified: reaction time, end of data acquisition time, total test time, turning time, turning time, going time, return time, the average of going and return acceleration, average of going and return speed, the average of going and return force, and the average of going and return power. In turn, with the Electrocardiography and Electroencephalography sensors, the following characteristics were identified: Heart rate variability, heart rate, the average amplitude of the QRS interval, the average amplitude of the RR interval, the average amplitude of the RS interval, frequency of the peaks of the Electroencephalography signal and variability of the electroencephalography signal peaks.

For the data analysis, different statistical methods were used, such as ANOVA, Pearson's correlation coefficient, and comparative tests, along with artificial intelligence methods, such as artificial neural networks.

However, these experiments revealed some limitations regarding the battery, limited storage, Internet connection for sending files to the server and Bluetooth connection for the acquisition of data from BITalino devices.

This study ended with the preliminary implementation of the artificial intelligence methods for detecting disease patterns and relating the different variables of Electrocardiography and Electroencephalography. Thus, we could verify whether it was possible to detect and identify diseases and age with the varying characteristics of the signal.

The concept of mobile Health has attracted considerable interest and has gained increasing importance from professionals from the related areas. This area will present major developments in the near future, and, with this work, we hope to contribute to it.

5.1. Future Work

The results obtained in this dissertation are promising. However, it is essential to increase the number of tests, and experiments should be carried out with a more diverse population from different regions of the country or even the world. For such an analysis, different signal characteristics of the various sensors must be calculated, trying to reduce the effects of Earth's gravity.

In continuation of the work initiated in this dissertation, other artificial intelligence methods will be implemented in addition to machine learning methods, such as Deep Learning, Adaboost, Support Vector Machine (SVM) and Decision Tree methods. Thus, better results can be obtained for detecting diseases and identifying the parameters of the Timed-Up and Go test.